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Abstract

The study aims to identify the indicators of corporate financial distress in the Indian industrial sector. The study begins by analysing the corporate bankruptcy filings and the outcomes of filings under the Insolvency and Bankruptcy Code (IBC), 2016. From the analysis of bankruptcy filings, a list of 82 publicly listed companies of industrial nature experiencing financial distress that have filed for bankruptcy under IBC is identified. Each of the 82 companies are paired with an equal number of matching financially sound companies to form a sample of 164 companies. The total samples are classified as training samples to identify the indicators and testing samples to validate the identified indicators. Further, 12 variables from the annual reports of the sample companies are analysed for a period of five years immediately preceeding the bankruptcy filing by the distressed companies. Simple regression analysis is employed for determining the primary indicator of corporate financial distress and logistic regression analysis is used to identify the supplementary indicator of corporate financial distress in the Indian industrial sector. The primary and the supplementary indicators are presented in the form of a two stage process to form the Corporate Distress Prediction (CDP) scorecard. The recommended CDP scorecard predicts financial distress in the Indian industrial sector at an accuracy ranging between 90 percent to 100 percent during the five years of study. The major implication of the study is that it can guide the corporate stakeholders in knowing the financial health of a company.

Keywords*:bankruptcy, financial distress, IBC, India, insolvency, scorecard*

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List of Acronyms

CDP	Corporate Distress Prediction Scorecard
CR	Current Ratio
DTAR	Debt to Total Assets Ratio
IBBI	Insolvency and Bankruptcy Board of India
IBC	Insolvency and Bankruptcy Code
ICR	Interest Coverage Ratio
NCLT	National Company Law Tribunal
NOCSR	Net Operating Cashflow to Sales Ratio
NOCTAR	Net Operating Cashflow to Total Assets Ratio
OPR	Operating Profits Ratio
PID	Proportion of Independent Directors
PPS	Proportion of Promoters Share
QR	Quick Ratio
ROA	Return on Assets
SWCR	Sales to Working Capital Ratio
TATR	Total Assets Turnover Ratio

1. Introduction

A business plays a vital role in the economic development of a country. Businesses offer products and services that provide jobs which create a stream of income and taxes, leading to better infrastructure that ultimately translates to business benefit. A healthy business thus contributes to the good health of the economy. Healthy businesses, small or large, result in improved quality of life and increased purchasing power among citizens. From the late 18th century, one of the important businesses that propelled the world to a new era has been Industries. Three major Industrial revolutions have transformed the world to the one we live in today. The industrial revolution begins with the mechanisation of manufacturing and the invention of the steam engine during the end of the 18th century. The second industrial revolution that transpired between 1870 to 1914 is the most important leap in human history. This revolution brought in mass production and saw the widespread adoption of early technology like telegraph, transportation and communication. The third industrial revolution during the early 1970s witnessed the advent of internet technology, renewable energy and information and communication technology. A high level of automation in the industries, Robotics, Artificial Intelligence (AI), Internet of Things (IoT) and digitalisation are ubiquitous today. Western countries like England, the US, Germany grew as a global power in the 19th and 20th centuries due to rapid industrialisation (Bulliet, Crossley, Headrick, & Johnson, 2014). For all the benefits that business and industrialisation bring to an economy, let us remember, there co-exist healthy and sick businesses. When businesses fail to maintain competitive efficiency, they get sick (Datta, 2013). Sick businesses leave a negative impact on the different stakeholder groups and the national economy at large. Employees, creditors, and investors are the most affected. Employees become redundant, creditors remain unpaid, and investors lose their investments when businesses fail.

1.1 Role of Industries in the Economic Development of Independent India

India was ruled by the British until 1947. India's share of the world economy declined from 22.6% in 1700 to 3.8% in 1952 (Livemint, 2019). When Britain grew rich, a pre-colonial Indian economy became impoverished due to British colonial rule (Roy, 2012). Pre-independence, there was no policy to promote the growth of Indian industry. In fact, government policies resulted in deindustrialisation. The economic policies transformed the country into a net supplier of raw materials and consumer of finished industrial products from Britain (Burange & Yamini, 2011). After gaining independence, India followed a path of

planned economic development. Industrial policies were framed and implemented. Industrial policy, 1945 being the first was later amended and came to be known as Industrial Policy Resolution, 1948. The other critical industrial policies that followed are Industrial policy Resolution, 1956, Industrial policy of 1977, Industrial Policy of 1980 and Industrial Policy of 1991. Under the industrial policies, the public sector was entrusted to lead the overall industrialisation, while private players were allowed to operate under comprehensive regulation and were controlled by the state. This comprehensive regulation and control, led to the sluggish and inefficient manufacturing sector. However, against the threat of imminent foreign exchange crisis, the new industrial policy was announced in July 1991which relaxed restrictions and removed several barriers to entry imparted by the controlled regime. The policy changes included the dismantling of the industrial licensing system, de-reservation of the industries to public sector, relaxing of restrictions on industrial investment and expansion, divestment of government equity in public sector enterprises and opening of industries for foreign direct investment. This comprehensive wave of deregulation was further accentuated in subsequent years (Dev and Veeramani, 2015). Thus, independence was not just for individuals but was also economic liberty.

1.2 Slowdown in the Indian Industrial Sector

The Indian economy has been one of the fastest-growing economies in the World. But, since 2015, a steep decline in industrial contribution to the country's GDP is experienced. As reported by the World Bank (2020), the growth rate of industrial contribution to GDP in India declined from 9.58 percent in 2015 to 1.84 percent in 2019, thus, marking a 81 percent decline in the growth rate over 5 years. According to the Index of Industrial Production (IIP), the different segments of the Indian industrial sector have recorded a decline in the growth rates since 2015. The growth rate in the mining sector has declined from 4.6 percent to 1.6 percent, manufacturing growth rate has declined from 2.4 percent to -1.4 percent, electricity sector registered a decline from 5.7 percent to 1 percent and the other industrial sectors growth rate fell from 3.3 percent to -0.8 percent by the end of March 2020. The weak industrial performance has been due to a combination of several factors. It includes policy uncertainties, high-interest rates, infrastructure bottlenecks, rising input cost and restrictive imports (Dev and Veeramani, 2015). As a result, an increasing number of companies in the industrial sector have defaulted credit and filed for bankruptcy during this period.

1.3 Insolvency Law in India

Insolvency and Bankruptcy Code (IBC) is the law that governs insolvency and bankruptcy in India, and National Company Law Tribunal (NCLT) is the adjudicating authority. Until the launch of IBC in December 2016, multiple legislations dealt with insolvency and bankruptcy like the Sick Industrial Companies Act (SICA), the Recovery of Debt Due to Banks and Financial Institutions Act (RDDBFI), the Securities and Reconstruction of Financial Assets and Enforcement of Security Interest Act (SARFAESI) and others (Kumar, 2019). The SICA governed the insolvency and bankruptcy proceedings in India since 1987. The Board of Industrial and Financial Reconstruction (BIFR) was established under SICA for the revival or the liquidation of sick companies. Company Law Board (CLB) was the adjudicating authority. Appeals against the order of BIFR was made before the Appellate Authority of Industrial and Financial Reconstruction (AAIFR). The banks and financial institutions also had the power to recover the collateral at default under the Recovery of Debt Due to Banks and Financial Institutions Act (RDDBFI), 1993. This act provided for the establishment of Debt Recovery Tribunals (DRT) for debt recovery by banks and financial institutions only. Debt Recovery Appellate Tribunals (DRATs) were also introduced as the appellate forum. Besides, under certain conditions, the Securities and Reconstruction of Financial Assets and Enforcement of Security Interest Act (SARFAESI), 2002 provided power to the secured creditors to take possession of the collateral without interference by the court. Further, out-of-court mechanisms were set up post-2000 to facilitate banks to restructure loan contracts with the debtors, and this led to the emergence of Corporate Debt Restructuring (CDR), Joint Lending Forum (JLF) and the Strategic Debt Restructuring (SDR) Forum (Kumar, 2019). Thus, multiple laws dealt with insolvency and bankruptcy and there was a need to bring all these laws under a single framework.

1.4 Insolvency and Bankruptcy Code (IBC), 2016

IBC was developed to "consolidate and amend the laws relating to reorganisation and insolvency resolution of corporate persons, partnership firms and individuals in a time-bound manner for maximisation of value of assets of such persons, to promote entrepreneurship, availability of credit and balance of interests of all the stakeholders including alteration in the order of priority of payment of government dues and to establish an Insolvency and Bankruptcy Board of India, and for matters connected therewith or incidental thereto" (Ministry of Law and Justice, 2016). The number of cases referred to NCLT under IBC is at a rise. Figure 1 presents the trend in bankruptcy filing under IBC for the quarter ending March 2017 to March

2020. From the figure, an upward trend in the bankruptcy filing is observed. The largest number of bankruptcy filings have been observed for the quarter ending January 2020. There has been an average of 1.4 times increase in the bankruptcy filings every quarter. According to John (2019) majority of the bankruptcy filings made under IBC mostly are from construction and from broader manufacturing industries comprising of metals, textiles, food and beverages and machinery, and equipment. Further, as reported by Insolvency and Bankruptcy Board of India (2020), from the date of inception of IBC in 2016 up to March 2020, a total of 3774 bankruptcy filings were made with NCLT. A vast majority of the filings are made under the manufacturing sector followed by real estate, construction, wholesale & retail trade, hotels & restaurants, electricity & others, transport, storage & communication. Of these, manufacturing, construction, and electricity belong to the industrial sector, undoubtedly making firms with industrial nature exposed to high risk of financial distress.

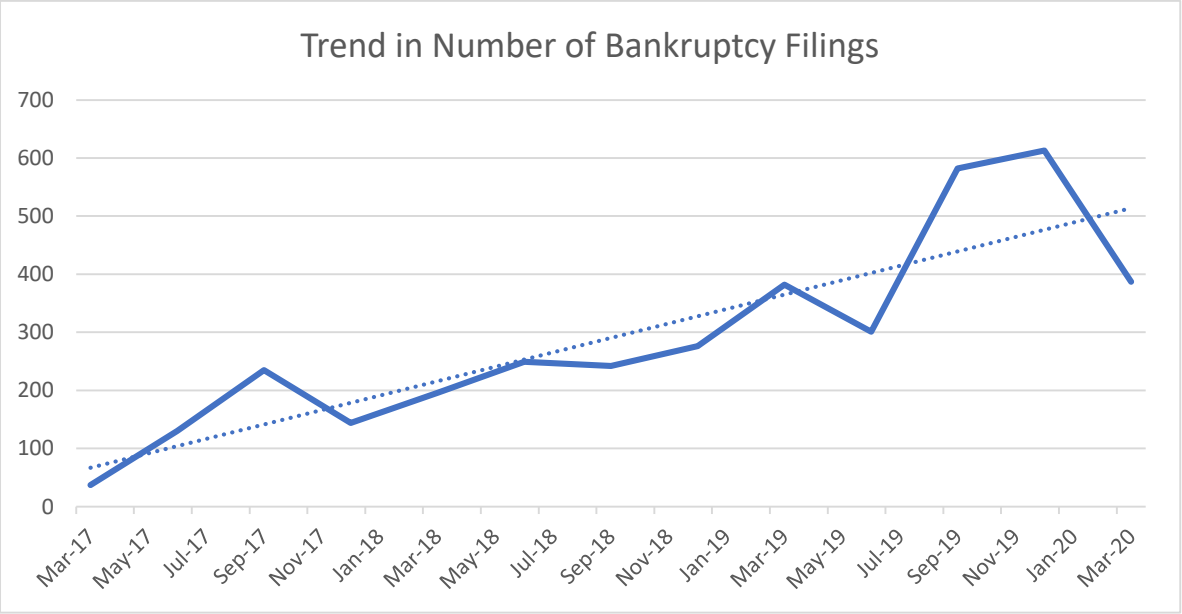

Figure 1.1: Trend in bankruptcy filings under IBC
Source: IBBI

1.5 Predicting Corporate Financial Distress

Many researchers have developed models to predict financial distress in business at an early stage, and historical financial ratios formed the basis for the models. It all began with Beaver (1966), who individually analysed financial ratios to discover the financial status of a business. Univariate analysis by Beaver was soon followed by Altman (1968), who analysed multiple variables simultaneously with the aid of statistical tool Multi Discriminant Analysis (MDA). Ohlson (1980) criticised MDA for the requirement of normally distributed data and, thus,

suggested a Logistic Regression model to predict the financial soundness of a company. All the models developed after that are an extension of the seminal works of Beaver, Altman, and Ohlson (Manzaneque, Merino & Priego, 2016). In India, Bandhopadhyay (2006), Datta (2013), Desai and Joshi (2015), Singh and Mishra (2016), and Agarwal and Maheshwari (2018), have formulated models to predict corporate credit default. Although these models were valuable, only financial ratios formed the basis for the formulation of these models. No attempts were made to determine the role of non-financial measures in predicting corporate financial distress. Also, the recommended models were developed before the inception of the new insolvency and bankruptcy law IBC in India. With the present rising number of bankruptcy filing under IBC, the significance of determining the indicators of financial distress has never been more important especially in the industrial sector. The current pandemic situation has further added to the need for exploring the indicators of corporate financial distress as a surge in bankruptcies is expected.

1.6. Statement of the Problem

An insolvency and bankruptcy law is a part of an authority's determination to protect property rights (Gratzer & Stiefel, 2008). In India, multiple laws have dealt with insolvency and bankruptcy until 2016. The rate of revival and restructuring of companies under these laws were poor, and the process of resolution and liquidation was prolonged. In 2016, a new bankruptcy law, Insolvency and Bankruptcy Code (IBC), was introduced with an overriding effect on all other laws concerning insolvency and bankruptcy. The new law aimed at speedy resolution and liquidation of loan defaults in India. It provides for a time-bound and market-linked resolution.

IBC is a creditor driven law where liquidation is mostly the outcome of insolvency and bankruptcy procedure. According to the law, failing to work out a resolution plan within the stipulated time frame results in the liquidation of the debtor company. The code rescues failing but viable corporate debtors and liquidates, failing and unviable ones. Since the inception of IBC, an increased number of companies are filing for bankruptcy, and the number of companies filing for bankruptcy in the industrial sector is very high. IBC being a creditor-oriented law, an increase in bankruptcy filings can lead to an increase in the number of liquidation.

Liquidation of business not only adversely affects the stakeholders but also has a severe impact on the nation's economy. When a business liquidates, employees become redundant, creditors remain unpaid, and investors lose their investments. When the number of liquidations

increases, consumer spending declines resulting in more businesses falling into financial troubles. Series of liquidations can result in a major economic crisis. Early detection of corporate financial distress can reduce the likelihood of bankruptcy filing and eventually prevent the business from liquidation and save the economy.

1.7. Need for the study

Under Insolvency and Bankruptcy Code 2016, a bankruptcy filing is made with the National Company Law Tribunal when a company defaults on servicing its debt. An operational creditor, financial creditor, or debtor can initiate bankruptcy filing. An analysis of the bankruptcy filings under IBC becomes necessary to know the nature and status of filings made under the new law. As IBC is creditor driven, an examination of the outcomes of bankruptcy filings is essential to learn the extent to which the IBC law favours the creditors.

An increasing number of bankruptcy filing in the industrial sector is a concern. Therefore, there is a need to formulate an early warning mechanism that can proactively predict the financial soundness of the companies belonging to the industrial sector. Early detection of the corporate financial distress can prevent the debtor company from prospective default and liquidation. Further, this mechanism can protect the stakeholders and the economy at large. An in-depth analysis of the essential elements of the financial statement of companies that have defaulted on credit and their comparison with non-defaulting companies is vital to identify the primary indicators of corporate financial distress. This can assist the stakeholders in distinguishing a financially distressed company from a financially sound company with ease.

As pointed by Scandizzo (2016), individual measures should not be discarded based on its standalone predictive power as the same variable, in combination with others, can exhibit an overall much higher predictive power. Similarly, different individual elements of a financial statement, when brought together, can demonstrate a strong ability to predict corporate financial distress. This idea necessitates the development of a multivariate model that can predict corporate financial distress at an early stage, which can facilitate timely corrective action and, thus, mitigate the risk of business failure.

1.8. Research Questions

The present study address questions like:

1. What is the status and outcome of bankruptcy filings in India under the new Insolvency and Bankruptcy law?

2. Is there any measure from the financial statement that significantly differentiates financially distressed companies from financially sound companies.

3. Do non-financial ratios improve the predictive efficacy of corporate financial distress prediction model?

4. How can a stakeholder differentiate a financially distressed company from a non-distressed company in the Indian industrial sector?

1.9 Research Objectives

The study is undertaken with the following specific objectives:

1. To classify and analyse the status and outcomes of corporate bankruptcy filings under IBC, 2016
2. To identify the measures that significantly differentiate financially distressed companies from financially sound companies in the Indian industrial sector
3. To investigate the role of non-financial measures in corporate financial distress prediction model.
4. To recommend the indicators of corporate financial distress in the Indian industrial sector.

1.11 Research Hypothesis

H_{01}: There is no statistically significant difference between the Return on Assets of financially distressed and financially sound companies

H_{02}: There is no statistically significant difference between the Operating Profits Ratio of financially distressed and financially sound companies

H_{03}: There is no statistically significant difference between the Current Ratio of financially distressed and financially sound companies

H_{04}: There is no statistically significant difference between the Quick Ratio of financially distressed and financially sound companies

H_{05}: There is no statistically significant difference between the Debt to Total Assets Ratio of financially distressed and financially sound companies

H_{06}: There is no statistically significant difference between the Interest Coverage Ratio of financially distressed and financially sound companies

H_{07}: There is no statistically significant difference between the Total Assets Turnover ratio of financially distressed and financially sound companies

H_{08}: There is no statistically significant difference between the Sales to Working Capital Ratio of financially distressed and financially sound companies

H_{09}: There is no statistically significant difference between the Cashflow to Sales Ratio of financially distressed and financially sound companies

H_{10}: There is no statistically significant difference between the Cashflow to Total Assets Ratio of financially distressed and financially sound companies

H_{11}: There is no statistically significant difference between the Proportion of Independent Directors of financially distressed and financially sound companies

H_{12}: There is no statistically significant difference between the Proportion of Promoters Share of financially distressed and financially sound companies

H_{13}: The Return on Assets of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{14}: The Operating Profits Ratio of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{15}: The Current Ratio of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{16}: The Quick Ratio of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{17}: The Debt to Total Assets Ratio of a business has a direct and statistically significant relationship with the probability of financial distress

H_{18}: The interest coverage ratio has an inverse and statistically significant relationship with the probability of financial distress

H_{19}: The Total Asset Turnover Ratio of a business has a statistically significant relationship with the probability of financial distress

H_{20}: The Sales to Working Capital Ratio of a business has a positive and statistically significant relationship with the probability of financial distress

H_{21}: The Cashflow to Total Asset Ratio of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{22}: The Cashflow to Sales Ratio of a business has an inverse and statistically significant relationship with the probability of financial distress

H_{23}: The non-financial ratios improve the efficacy of corporate financial distress prediction model

1.12 Operational Definition

a. Financially distressed company: Company that has defaulted on the credit and thus, bankruptcy filing has been made against the company with the National Company Law Tribunal (NCLT) under The Insolvency and Bankruptcy Code (IBC), 2016.

b. Financially sound company: Any company against which there is no bankruptcy filing with National Company Law Tribunal (NCLT) under The Insolvency and Bankruptcy Code (IBC), 2016 during the study period.

c. Return on Assets: It is the ratio of net profits after taxes and average total assets.

d. Operating Profit Ratio: It is the ratio of operating profit (EBIT) to sales.

e. Current Ratio: It is the ratio of current assets to current liabilities.

f. Quick Ratio: It is the ratio of quick assets to current liabilities. Quick assets are the difference between current assets and inventories.

g. Debt to Total Assets Ratio: It is the ratio of total debt by total assets of a business enterprise.

h. Interest Coverage Ratio: It is the ratio of Earnings Before Interest and Taxes (EBIT) by outstanding interest.

i. Total Assets Turnover Ratio: It is the ratio of sales to total assets of the business.

j. Working Capital Turnover Ratio: It is the ratio of sales to the working capital of a business.

k. Cash flow to Sales: It is the ratio of cash flow from operating activities to sales revenue.

l. Cash flow to Total Assets: It is the ratio of cash flow from operating activities to total assets of the company.

m. Proportion of Independent Directors: It is the ratio of number of independent directors to the total number of director in the company board.

n. Proportion of Promoters Share: It is the ratio of the number of shares held by the promoters to the total number of outstanding shares of a company.

2. Review of Literature

2.1 Default, insolvency, bankruptcy, and financial distress defined

Corporate credit default is a global challenge today. The term default must be differentiated from insolvency and bankruptcy. When the debtor fails to repay the credit, he is said to be in

default. The default may be either due to his inability or unwillingness to pay. On the other hand, insolvency exclusively refers to the inability of the debtor to repay the credit. Whereas, bankruptcy is a legal finding that imposes court supervision over the financial affairs of those who are insolvent or in default. Insolvency is necessary but not an adequate condition for bankruptcy (Gratzer & Stiefel, 2008). According to Platt & Platt (2006), the term financial distress & bankruptcy are also different. Financial distress happens to companies whose operating decisions perform below expectations. On the other hand, bankruptcy is a result of excessive debt levels. Thus, it can be agreed that high leveraged firms when face financial distress become insolvent, thereby landing in bankruptcy.

2.2 Causes of Business failure

A study by Ooghe & Prijcker (2008), analyses the causes for business failure based on four types of failures using the case study method. First, start-up businesses fail due to inadequate experience in the industry. Second, growing businesses fail due to managers hunger for high risk. Third, dazzled growth businesses fail due to magnified risk and ignorance towards managerial and operational risk. Finally, established companies fail due to a lack of commitment and motivation to adjust to the changing reality. While Ooghe & Prijcker (2008), mostly blame the management for business failure, Gratzer & Stiefel (2008), considers both internal and external factors and points at the following three reasons for business failure. First, businesses fail due to poor management accusing the managerial personnel of a lack of knowledge, experience, and competence in management, resulting in the fall of the business. Second, the financial soundness of the business can pose a threat to survival, and finally, macro-economic factors like business cycles, interest rates, and taxes can adversely affect the health of the business.

2.3 Bankruptcy law

According to Gratzer & Stiefel (2008), bankruptcy law is essential for declaring an entity bankrupt. In the absence of bankruptcy law, there would be a race among creditors for the debtor's assets. A bankruptcy filing can be voluntary or involuntary. The debtor initiates the filing in the former, and the creditor initiates in the latter. The creditor can be a financial creditor like banks and financial institutions or operational creditors like the supplier or employee. Some countries have debtor-oriented bankruptcy law, while some have creditors favouring bankruptcy law. Though Creditor friendly law and debtor-friendly law appears to be mostly opposite, there exists a continuum of bankruptcy law systems between these two

polar cases. The law favouring the debtor intends to provide them a fresh start through reorganisation and mergers while countries with creditor favoring bankruptcy codes, liquidation is the typical outcome of corporate insolvency proceedings. In countries with debtor-oriented bankruptcy law, filing for bankruptcy does not mean the lapse of going concern concept as the law encourages companies to continue as going concern during financial difficulties (Yu & He, 2018). Froute (2007) points out an association between the leniency of judges and companies filing for bankruptcy. He says the higher the proportion of lenient judges in the economy, the smaller will be the number of bad companies hesitating to go for trial and bigger the probability that the project submitted to creditors is profitable. Court behaviour has a direct impact on the profitability of the project, and by privileging debtors, the situation of creditors improves. On the other hand, a study by Gennaioli & Rossi (2010) points out that strong creditor protection improves judicial incentives for reorganisation and thus resolve financial distress efficiently.

2.4 Bankruptcy law in India

In India, The Insolvency and Bankruptcy Code (IBC), 2016, is single umbrella legislation that governs the insolvency and bankruptcy proceedings. IBC aims at speedy resolution or liquidation of loan defaults. The Insolvency and Bankruptcy Code was introduced in the Lok Sabha on 21 December 2015; the standing committee gave its report on 28 April 2016, it was passed by the Lok Sabha on 5 May 2016, Rajya Sabha on 11 May 2016 and the final assent of the president of India was received on 28 May 2016 (Goel, 2017). The code was needed to reduce the time taken to resolve insolvency, develop investor confidence, avoid confusion caused by a complex judicial framework, address the NPA situation decisively and to develop the credit and bond market in India (Diwanji, 2016). In IBC creditor is king. It is creditor driven, and the creditors take control of the board/assets of debtor. In other words, Insolvency Professional (IP) takes charge of the assets on behalf of the creditors (Krishan, 2018).

2.5 Financial Distress Prediction Models

Researchers have developed a range of models to predict business failure. The models are popularly called as Financial Distress Prediction Models or Bankruptcy Prediction Models or Credit Default Prediction Models. The prediction models developed hence facilitate early detection of financial distress, which can further reduce the risk of bankruptcy. In the past, numerous researchers have proposed many models that predict the financial status of businesses. All models developed are an extension to seminal works of Beaver, Altman, and

Ohlson (Manzaneque, Merino & Priego, 2016). Financial ratios formed the basis for the models developed by Beaver, Altman, and Ohlson. Individual analysis of ratios was the first method used in bankruptcy prediction by Beaver in 1966. The study concluded that the ratio distribution exhibited marked deterioration as failure approached, thus widening the gap between failed and non-failed firms. The use of Univariate analysis was soon followed by multivariate analysis. Altman (1968), in his work, stressed that individual variables are susceptible to faulty interpretation and are potentially confusing. After careful consideration, he chose Multiple Discriminant analysis (MDA) as an appropriate statistical technique to analyse five financial ratios to discriminate between bankrupt and non-bankrupt firms. Ohlson (1980) criticised the MDA approach stating that the requirement of normally distributed predictors can limit the scope of the investigation. His study based on nine financial ratios used Logistic Regression analysis for multivariate analysis of financial ratios in predicting bankruptcy. Following this, many financial distress prediction models were developed across the globe. Besides statistical tools used for analysis, these models differed in sample design and variables selection.

Samples in default prediction studies consist of defaulting and non-defaulting companies. While most studies considered matching paired design, where every defaulting company paired with a matching non-defaulting company, few studies adopted the unmatched sample. In the case of a matched pair design, researchers have often considered industry type and firm size of a defaulting company to identify a matching non-defaulting company. However, the definition of firm size differed amongst the researchers. While most researchers like Beaver (1966), Altman (1968), Deakin (1982), Aziz (1988), Rashid & Abbas (2011) Singh & Mishra (2016) and others considered the total asset size as firm size, Ugurlu & Aksoy (2006) used market capitalisation to be the firm size and according to McGurr & DeVaney (1998) and Blum (1974) sales revenue was the indicator of firm size. However, Ohlson (1980) opined that industry and firm size does not serve the matching purpose; instead, it would be fruitful to use them as predictors. The other criteria considered for matching include employee count, net worth, and indebtedness ratio, respectively by Blum (1974), Dilip Kumar Datta (2013), Durica & Adamko (2016). Hensher & Jones (2007) and Pervan, Pervan, & Vukoja (2011), apart from industry-wise pairing, randomly selected the non-defaulting companies for their study without any further criteria. Researchers differed not just in the choice of criteria for matching the defaulting companies with non-defaulting ones but also with the period during which the criteria were matched. For instance, while some researchers matched the criteria

(say asset size) for all the periods of study (say three years), others matched the criteria only for the year when the company defaulted payment or the year immediately preceding the default. In the case of the unmatched sample, the sample size is relatively huge, as displayed by Jones & Hensher (2004); Ohlson (1980) and Altman & Sabato, where the sample size is over 2000 units. As rightly pointed by Ohlson (1980), in the case of large samples, the estimates are not too sensitive to any specific samples used and therefore produce the smallest possible error of the estimated coefficient.

In the financial distress prediction models, variables include dependent and independent variables, also known as response and predictor variables. The dependent variable is mostly, a dichotomous variable and can have the value 0 or 1, i.e., defaulting or non-defaulting, respectively. However, Jones & Hensher (2004) mentions 0, 1 and 2 mutually exclusive categories where 0 indicates firms that are going concerns and show no evidence of financial distress, 1 indicates firms that are going concern but have experienced financial difficulties while 2 indicates firms that are no longer going concerns. Financial ratios of the corporations under study often constitute the independent variables. Profitability, liquidity, leverage, efficiency, and cash flow ratios are commonly used in financial distress prediction models.

Return on Assets (ROA) and Operating Profit Ratio (OPR) are the two profitability ratios considered for the study. ROA is used by Singh & Mishra (2016) to develop a bankruptcy prediction model, and Bandyopadhyay (2006), have used OPR in developing credit default prediction model in India. Both ratios have proved to have a significant negative association with the event of financial distress in the respective studies. Current Ratio (CR) and Quick Ratio (QR) are the most widely used liquidity ratios. Pervan, Pervan, & Vukoja (2011) used the CR ratio to predict company bankruptcy in Croatia. Waqas & Md-Rus (2018) identified QR as a significant predictor of financial distress for Pakistani firms. Both the liquidity ratios have shown a negative association with the probability of occurrence of financial distress. Debt to Total Assets Ratio (DTAR) and Interest Coverage Ratio (ICR) are the measures of leverage in the study. Shetty, Pakkala, & Mallikarjunappa (2012) have established a significant positive association of DTAR with the bankruptcy in IT/ITES companies in India. Datta (2013), while determining industrial sickness in India, considered ICR and found it to be inversely associated with industrial sickness. Total Asset Turnover Ratio (TATR) and Sales to Working Capital Ratio (SWCR) are the two measures of efficiency considered in the study. Rashid & Abbas (2011) recognises TATR to be negatively significant in predicting bankruptcy in Pakistan. Obradovic, Jaksic, Rupic, & Andric (2018) observe SWCR to be

positive and significantly associated with corporate financial distress in Turkey. Cashflow to Sales Ratio (CSR) and Cashflow to Total Assets Ratio (CTAR) measures the efficiency of cashflows. Obradovic, Jaksic, Rupic, & Andric (2018) and Waqas & Md-Rus (2018) identifies CSR and CTAR, respectively, to be negatively associated with the event of bankruptcy. In recent years' researchers argue that in addition to financial ratios, the use of non-financial ratios improves the predictive efficacy of the model. A study by Liang, Lu, Tsai & Shih (2016) investigated the role of non-financial variables in predicting bankruptcy in Taiwan. Seven and five categories of financial and non-financial measures were used, respectively. Financial ratios consisted of solvency, profitability, cash flow capital structure, turnover, growth, and other ratios. Board structure, ownership structure, cash flow rights, retention of key personnel, and others constituted the non-financial variables. The study concluded that the model with both financial and non-financial ratios performed better in predicting bankruptcy.

2.6 Research Gap

The Insolvency and Bankruptcy Code (IBC) is new legislation that governs insolvency and bankruptcy in India. It was introduced in 2016. Until then, the Sick Industrial Companies Act (SICA) primarily dealt with insolvency and bankruptcy. Therefore, studies in the past have mostly focused on the filings under SICA. No past research has made an in-depth analysis of the bankruptcy filings and the outcomes of bankruptcy filings under IBC.

While research in bankruptcy has been extensive especially relating to developing new models or validating existing models, no studies in the past have studied the characteristics of corporate financial distress by individually analysing the elements reported in the financial statements of financially distressed companies and compared it with the financially sound companies. Further, though researchers have recommended numerous bankruptcy prediction models in the past, the major limitation of the existing literature is that no studies in the Indian context considered the role of board and ownership structure in the process of formulating the model. The resulting two stage distress prediction model is unique to this study.

3. Research Methodology

3.1 Sample

The sample consists of two groups of companies, financially distressed and financially sound companies. Companies that have defaulted on credit and thus has filed for bankruptcy under IBC, 2016 since its inception to 31 March 2019 are classified as financially distressed companies. Companies that have not filed for bankruptcy during the period are treated as afinancially sound companies. Table 3.1 summarises the selection of defaulting companies.

Table 3.1: Sample selection

Total number of firms filing for bankruptcy under IBC	**1756**
Less: Private Limited Companies	1154
Public Limited Companies	**602**
Less: Public Companies not of industrial nature	118
Industrial Corporations	**484**
Less: Unlisted industrial corporations	321
Publicly listed industrial corporations	**163**
Less: Non-availability of data	81
Publicly listed industrial corporations with required data availability	**82**

The sample companies belong to the industrial sector as classified by National Industrial Classification (NIC) - 2008 published by Central Statistical Organisation (CSO), the Ministry of Statistics and Programme Implementation, Government of India. The industrial sector comprises of manufacturing, construction, mining & quarrying and electricity, gas, steam and air conditioning. The industrial classification of sample defaulting companies are presented in table 3.2

Table3.2: Industrial classification of sample defaulting companies

Industry	**Number**
Manufacturing	69
Construction	12
Electricity, gas, steam & air conditioning	1
Total	82

For every financially distressed company, a matching financially sound company is selected. Industry type and asset size are the criteria used for matching the defaulting companies with non-defaulting companies. An independent sample t-test is conducted to compare the mean asset size of the two groups of companies. The results of the independent sample t-test is presented in table 3.3. Results of the mean comparison test reveal that at 5 percent level of significance there is no statistically significant difference between the asset size of the two sets of companies, thus, confirming a matched pair sampling design.

Table 3.3: Results of mean comparison test

Group	Obs	Mean	Std Err	Std Dev	[95% Conf.	Interval]
0	82	7032.26	2626.53	23784.22	1806.294	12258.23
1	82	4416.96	1107.32	10027.2	2213.738	6620.173
					t=	0.9175
					df=	162
					Pr(|T| > |t|) =	0.3602

3.2 Variables

Table 3.4: List of Variables	Code
Financial Status (Financially distressed = 1, Financially sound = 0)	FS
Return on Assets	ROA
Operating Profits Ratio	OPR
Current Ratio	CR
Quick Ratio	QR
Debt to Total Assets Ratio	DTAR
Interest Coverage Ratio	ICR
Total Asset Turnover Ratio	TATR
Sales to Working Capital Ratio	SWCR
Net Operating Cashflow to Sales Ratio	NOCSR
Net Operating Cashflow to Total Assets Ratio	NOCTAR
Proportion of Independent Directors	PID
Proportion of Promoters Share	PPS

The financial status and the financial and non-financial measures constitute the variables for the study. The financial status is a binary variable. assuming the values 1 or 0, indicating financially distressed and financially sound, respectively. Ten financial ratios representing liquidity, profitability, activity, efficiency, and cash flows are taken for the study. Two non-financial ratios representing board composition and ownership structure also considered in the study. Table 3.4 presents the list of variables and their codes.

3.3 Data Collection

Secondary data forms the basis for the study. The list of companies filing for bankruptcy under IBC, 2016, and its status is collected from the IBBI website by analysing each order passed by the different benches of NCLT since the inception of IBC to 31 March 2019. The Judgement of corporate insolvency and bankruptcy process declared until 31 March 2020 are considered for analysing the outcomes of bankruptcy filing under IBC 2016.

The financial and non-financial ratios for both defaulting and non-defaulting companies are collected for a period of five years immediately preceding the filing of bankruptcy by the defaulting companies. Data on independent variables are collected from the corporate database Ace Anayzer and CMIE Prowess. Data for every year ending 31 March was considered for the study.

3.4. Statistical tool for analysis

A range of exploratory, descriptive and inferential statistical tools are used for analysis in the study. The status and outcome of bankruptcy filings under the new insolvency and bankruptcy code are analysed using the exploratory statistical tool. The stacked bar graph is the tool used for visualising data exploration. The length of the smaller boxes represents the percentage of cases in each category of the variable (Aldrich & Rodríguez, 2013). Stacked bar graphs are used in the current study to display bench wise bankruptcy filing and outcomes, bankruptcy filing and outcome based on the type of petitioner, sectoral classification of bankruptcy filing and outcomes and finally industrial classification of the bankruptcy filing and its outcome under IBC. Microsoft Excel is used for tabulation and presentation.

The financial and non-financial ratios for sample companies are summarised with the aid of descriptive statistical tools like arithmetic mean, and standard deviation and the association between these variables are examined using correlation. Descriptive statistics is the starting point for data analysis that allows to organise, simplify and summarise the data. It describes

the basic characteristics of the data under study (Allen, 2017)**.** The arithmetic mean is obtained by dividing the total of the values of each ratio by the total number of samples in each set of companies. But, arithmetic mean fail to give an idea about the scatter of the values of items of a variable in the series around the true value of average. In order to measure this, standard deviation, an important measure of dispersion is computed. Standard deviation is defined as the square root of the average of squares of deviations when such deviations for the values of individual items in a series are obtained from the arithmetic average (Kothari, 2004). In the present study, arithmetic mean and standard deviation of each predictor variable is computed for the period of five years for the two groups of companies using statistical software Stata. The minimum and maximum value of each ratio is also provided under descriptive analysis.

Dummy variables regression model is employed for determining the primary indicators of financial distress in the industrial sector. A balanced panel of data with random effects is used to arrive at the primary indicators of financial distress. The baseline model is

$$y = \beta_0 + \beta_1 x_{it} + \varepsilon_{it}$$

Originally, in a regression model β_1 represents a slope indicating the change in the dependent variable for a unit change in the independent variable. In the present study, to determine the primary indicators, the financial status of the company is the independent variable, and individual financial and non-financial ratios are the dependent variables. What does β_1 represent in a dummy variables model? β_1 indicates the change in the dependent variable (ratios) when the financial status of a company changes from financially distressed to financially sound or vice versa.

Under this model, the expected value of ratios for a financially distressed company is

E (Value of dependent variable of distressed company = 1) = $\beta_0 + \beta_1 * 1 = \beta_0 + \beta_1$

And the expected value of ratios for a financially sound company is

E (Value of dependent variable for non-distressed company = 0) = $\beta_0 + \beta_1 * 0 = \beta_0$

The following models are formulated to determine the primary indicators of corporate financial distress and its expected value for the two groups of companies.

$$ROA_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \qquad (1)$$

$$OPR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \qquad (2)$$

$$CR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (3)$$

$$QR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (4)$$

$$DTAR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (5)$$

$$ICR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (6)$$

$$TATR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (7)$$

$$SWCR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (8)$$

$$NOCSR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (9)$$

$$NOCTAR_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (10)$$

$$PIP_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (11)$$

$$PPS_{it} = \beta_0 + \beta_1 FS_{it} + \varepsilon_{it} \quad (12)$$

Logistic regression analysis is the statistical tool employed to develop a model that distinguishes a defaulting company from a non-defaulting company. In logistic regression models, the regression weights are computed based on maximum likelihood estimation, which is an iterative estimation process that finds the optimum set of regression weights (Schumacker, 2015). Logistic Regression makes the following key assumptions

1. It does not assume a linear relationship between the dependent and independent variables.

2. Dependent variable values do not need to be normally distributed.

3. There is no homogeneity of variance assumption among or within categories.

4. Normally distributed error terms are not assumed.

5. Independent variables need not be measured on the interval scale.

6. There are no missing data in the contingency table (Schumacker, 2015)

The present study employs binary logistic regression. Two binary logistic regression models Model 1 (M1) and Model 2 (M2) are developed using statistical software package Stata. In a binary logistic regression where the dependent variable assumes the value 1 or 0, logistic regression models the probability of Y=1 as a function of predictor variables. The standard logistic function is given below

$$\text{Log}\ \frac{P(Y)}{1-P(Y)} = \beta_0 + \beta_1 X_{1+}\ \beta_2 X_2 \ldots\ldots + \beta_n X_n$$

Taking the exponential on both sides and then solving for P gives

$$P_Y = 1 / [1 + e^{-z}]$$

where: P_Y: Probability of financial distress

e: the base of the natural logarithm, e=2.71828

z: $\beta 0 + \beta 1 X i 1 + \ldots\ldots + \beta n Xin$

β_1- β_n: coefficients of predictor variables

X_1-X_n: Predictor variables

Here, the dependent variable is binary assuming the values 1 or 0, indicating financially distressed and financially sound, respectively. Independent variables or predictor variables comprise of both financial and non-financial measures.

3.5 Scope of the Study

Bankruptcy filings made under the Insolvency and Bankruptcy Code, 2016, since the inception of IBC in 2016 up to 31 March 2019 forms the basis for the study. Only publicly listed industrial corporations, as defined by the Ministry of Statistics and Programme Implementation, Govt of India are considered for the study. Industrial corporations include manufacture, mining & quarrying, electricity, gas, and air conditioning supply and construction companies. Non-industrial companies like financial corporations, education, information & communication, accommodation and food services, real estate, and others are excluded from the study as they differ in characteristics from the industrial corporations. Also, industrial corporations should be publicly listed in India. Twelve variables, consisting of ten financial ratios, every two ratios representing liquidity, profitability, leverage, efficiency, and cash flow, along with two non-financial ratios are considered for the study. The data is collected and analysed for five years immediately preceding bankruptcy filing by the company.

3.6 Conceptual Framework

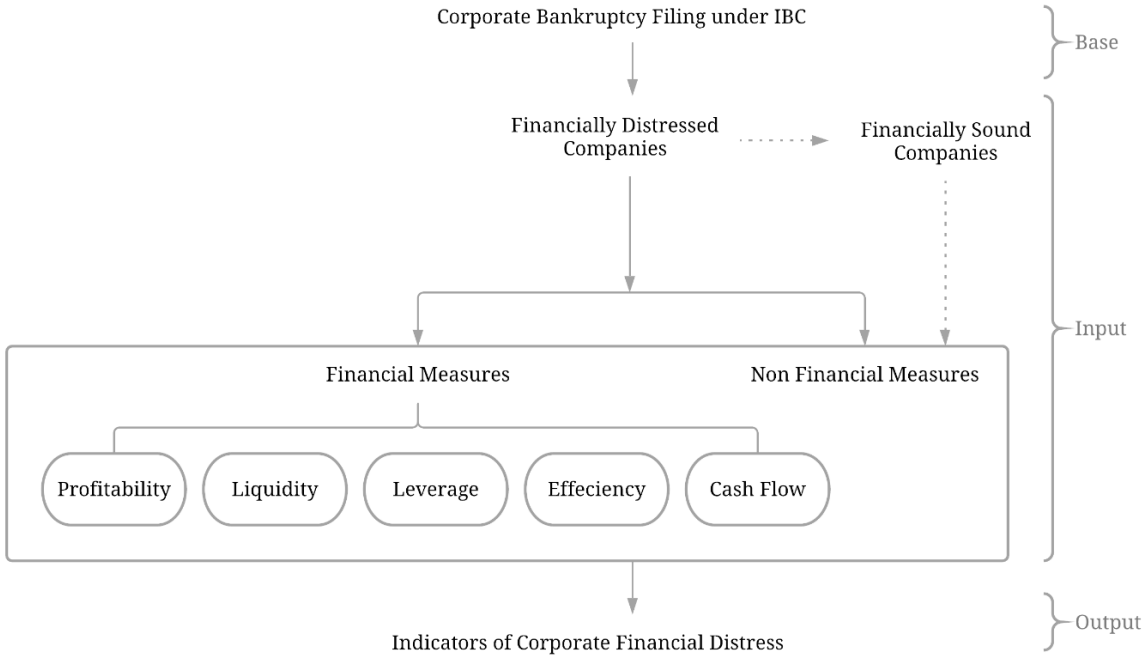

Figure 3.1 Conceptual framework of Indicators of Corporate Financial Distress

4. Data Analysis and Interpretations

4.1 Objective 1: To classify and analyse the status and outcomes of bankruptcy filings under IBC, 2016

The law that governs insolvency and bankruptcy in India is Insolvency and Bankruptcy Code, 2016. In case of any corporate default, the financial creditor or operational creditor or debtor company makes the bankruptcy filing. The present study assesses the status and outcomes of bankruptcy filing under IBC. The status of the filings made until March 2019 and the verdicts for the filings made until 31 March 2020 are analysed. The outcome of bankruptcy filing is classified into three categories, liquidation, resolution, and others. 'Others' include all other cases apart from liquidation and resolution. It consists of withdrawal and dismissal of the case, extension provided, and pending status. Table 4.1 presents a summary of the status and outcomes of bankruptcy filings under different NCLT benches.

Classification of bankruptcy filings and outcomes based on NCLT benches

Table 4.1: NCLT bench wise filings & outcome

Name of the Bench	Filing Status	Outcomes		
		Liquidation	Resolution	Other
Principal Bench Delhi Bench	411	135	26	250
Ahmedabad Bench	121	65	14	42
Allahabad Bench	46	14	2	30
Bengaluru Bench	54	26	7	21
Chandigarh Bench	104	42	16	46
Chennai Bench	260	131	27	102
Guwahati Bench	7	1	4	2
Hyderabad Bench	113	45	10	58
Kolkata Bench	175	79	31	65
Mumbai Bench	454	172	35	247
Jaipur Bench	11	4		7
Cuttack Bench	-	-	-	-
Kochi Bench	-	-	-	-
Amravati Bench	-	-	-	-
Indore Bench	-	-	-	-
Total	1756	714	172	870

Source: NCLT orders extracted from IBBI website

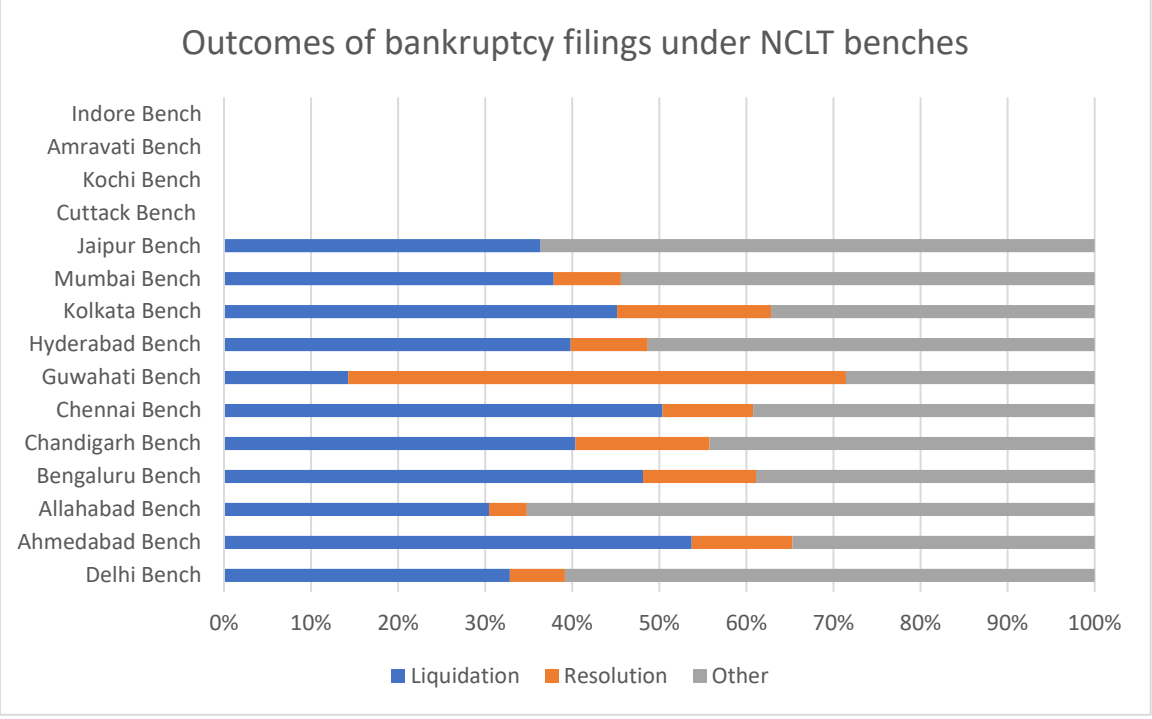

Figure 4.1: Filings with NCLT benches

Bankruptcy filings in India are made with NCLT. There was a total of twenty-five NCLT benches until March 2019. Four benches in New Delhi, three in Mumbai; Kolkata, Chennai, Chandigarh, Jaipur, and Hyderabad have two benches each and Ahmedabad, Allahabad, Bengaluru, Guwahati, Cuttack, Kochi, Amaravati and Indore have one bench each. As high as 26 percent of the total bankruptcy filings belonged to the Mumbai bench. Mumbai and Delhi benches put together had 49 percent of the total filings. Table 4.1 reveals that the number of liquidations is far higher than the number of resolutions under IBC. Of the total liquidations made, the maximum number of liquidation decisions are passed by the Mumbai benches followed by Delhi benches and the Chennai bench, which together constitute over 60 percent of the total liquidations made. However, under the Guwahati bench, four out of the seven cases filed have been resolved, and only one company is liquidated. Here, the percentage of resolution is about 57%, and liquidation is only 14%.

Annual classification bankruptcy filings and outcomes under IBC

Table 4.2 presents the annual bankruptcy filings, along with the corresponding outcomes. The trend in bankruptcy filings under IBC indicates an increase in the number of filings year after year. Trend analysis of outcomes reveals that the overall number of liquidations is increasing year after year, while the number of resolutions is declining. The number of resolutions has halved during the year ended 2019 as compared to 2018. The number of cases belonging to the category 'others' has increased during the three years.

Table 4.2: Annual filings and outcomes

Outcome	2016-17	2017-18	2018-19	Total
Liquidation	22	333	359	714
Resolution	8	110	54	172
Other	5	240	625	870
Total Annual Filings	35	683	1038	1756

Source: NCLT orders extracted from IBBI website

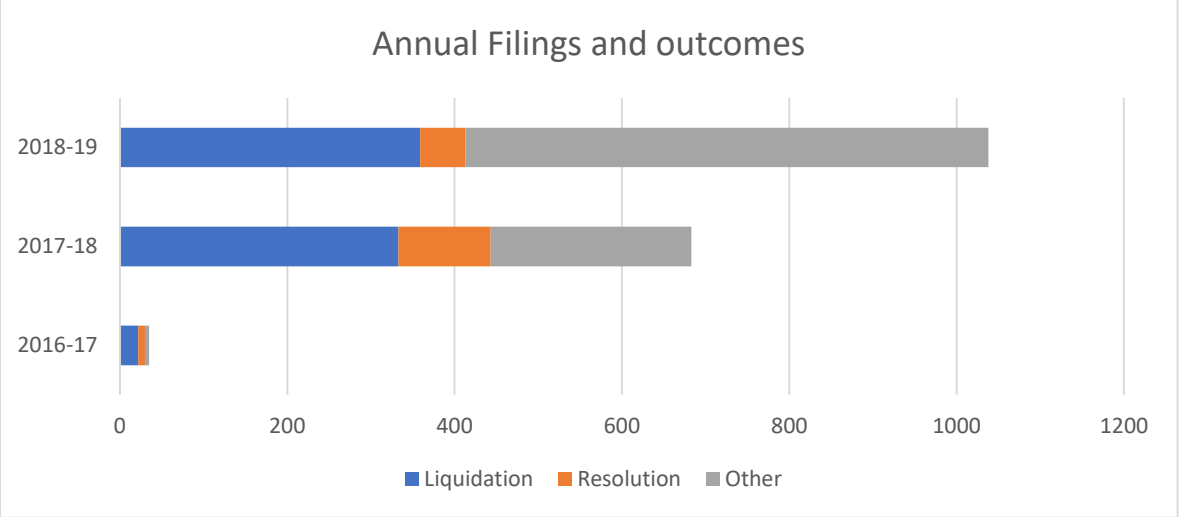

Figure 4.2: Annual Corporate IBC filings and outcomes

Classification of Bankruptcy filings and outcomes on the basis of type of petitioner

The total number of bankruptcy filings made until 31 March 2019 are 1756. Of the 1756 filing, as high as 830 filings are made by operational creditors, 748 by financial creditors and 178 by debtors. Therefore, about 47 percent of the filings are initiated by operational creditors, followed by financial creditors constituting about 43 percent of the filings, and lastly, about 10 percent of the filings are made by corporate debtors.

The percentage of liquidation to the total number of filings made by financial creditors is over 40 percent as against about 37 percent by operational creditors. On the other hand, about 12 percent of the filings made by financial creditors have been resolved against over 6 percent resolutions when operational creditors make the petition. In the case of filings made by the debtor company, 60 percent of the companies experienced liquidation, 16 percent of the companies have seen resolution, and 24 percent of the cases belong to the 'other' category. Table 4.3 presents the number of filings made by each type of petertioner and the associated outcomes.

Table 4.3: Filings & outcomes based on the type of petitioners

Petitioner	Liquidation	Resolution	Other	Total
Corporate Debtor	107	28	43	178
Financial Creditor	302	89	357	748
Operational Creditor	305	55	470	830
Total	714	172	870	1756

Source: NCLT orders extracted from IBBI website

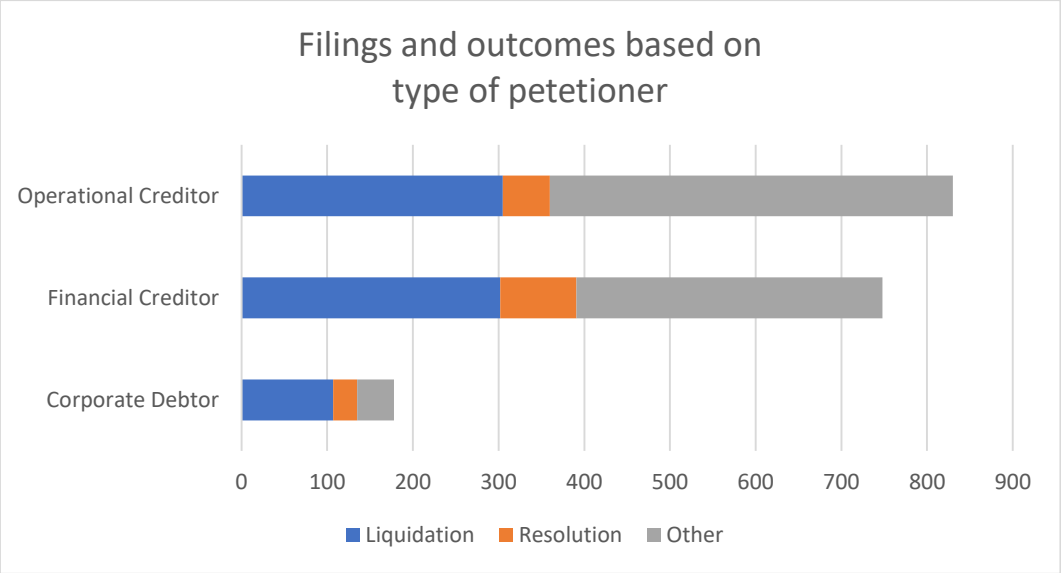

Figure 4.3: Filings & outcomes based on the type of petitioners

Industrial classification of bankruptcy filings and outcomes under IBC

According to table 4.4, in the public sector, firms of industrial nature have seen maximum filings. Amongst these filings, manufacturing industry constitutes over 75 percent of the total industrial filings followed by the construction industry and industry dealing with electricity, gas, steam & air conditioning supply. Manufacturing and construction industries put together to make over 72% of the total filings amongst public sector companies. The manufacturing industry, the industry with the maximum number of filings under the public sector, had over 40 percent of companies liquidated, and about 19 percent resolved. In fact, in all industries, the number of liquidations far exceeded the number of resolutions except the accommodation and food services industry, with a total of 11 filings observed liquidation and resolution of two companies each.

Table 4.4: Industrial classification of filings & outcomes

Section	Industry	Total	Liquidation	Resolution	Others
A	Agriculture, forestry & fishing	-	-	-	-
B	Mining & Quarrying	19	5	4	10
C	Manufacture	367	150	70	147
D	Electricity, gas, steam & air conditioning	30	12	4	14
E	Water supply; sewerage, waste management & remediation activities	3	-	-	3
F	Construction	69	23	4	42
G	Wholesale & Retail Trade	27	18	1	8
H	Transportation & Storage	8	4	1	3
I	Accommodation & food service activities	11	2	2	7
J	Information & Communication	35	10	1	24
K	Financial & Insurance Activities	9	6	-	3
L	Real estate activities	3	1	-	2
M	Professional, scientific & technical act	9	5	-	4
N	Administrative & support activities	2	-	-	2
O	Public Administration & Defence	-	-	-	-
P	Education	2	1	-	1
Q	Human Health & Social work activities	3	-	1	2
R	Arts, entertainment & recreation	2	-	-	2
S	Other Services	-	-	-	-
T	Activities of households as employers	-	-	-	-
U	Activities of extraterritorial organisations & bodies	3	-	-	3
	Total	602	237	88	277

Source: NCLT orders extracted from IBBI website

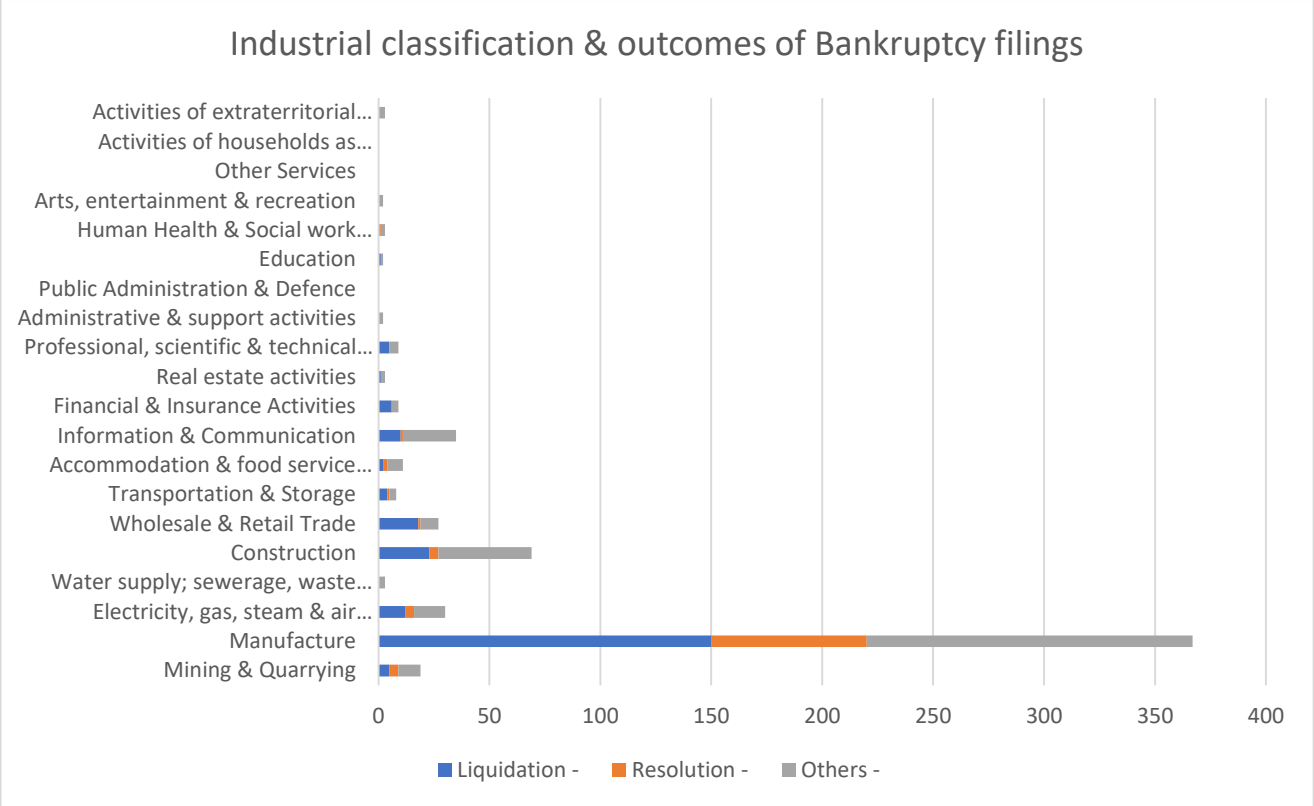

Figure 4.4: Industrial classification of filings & outcomes

4.2 Objective 2: To identify the measures that significantly differentiate financially distressed companies from financially sound companies in the Indian industrial sector

Table 4.5 : Descriptive Statistics of Variables

	Financially Distressed Companies					Financially Sound Companies			
Variable	Obs	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
ROA	410	4.278	5.677	-25.298	35.370	-10.570	19.581	-129.950	55.880
OPR	410	0.125	0.152	-0.485	1.107	-9.740	92.322	-1416.000	3.669
CR	410	1.843	2.056	0.349	18.240	0.859	0.557	0.000	5.360
QR	410	1.305	1.786	0.052	14.740	0.549	0.389	0.000	2.800
DTAR	410	0.835	5.149	-38.244	51.179	0.727	0.675	0.000	8.692
ICR	410	30.594	275.496	-289.765	5273.411	-9.628	65.321	-699.840	90.985
TATR	410	1.135	0.849	0.067	7.460	0.691	0.704	0.000	4.328
SWCR	410	15.601	106.100	-371.966	1356.799	1.736	26.873	-141.258	355.015
NOCSR	410	0.104	0.279	-0.747	4.713	18.666	355.458	-198.379	7170.000
NOCTAR	410	0.078	0.102	-0.200	1.222	0.027	0.110	-0.592	0.790
PID	410	0.508	0.091	0.000	0.727	0.505	0.161	0.000	1.000
PPS	410	0.593	0.173	0.000	1.000	0.495	0.182	0.000	0.990

The descriptive statistics of financial and non-financial measures are presented in Table 4.5. From the table, it is evident that excepting NOCSR, the mean ratios of financially sound companies are higher than financially distressed companies. High NOCSR among the financially distressed group is due to a single sample company with extremely poor sales but very high cashflows for the two years immediately preceding the bankruptcy filing. In spite of very low sales, high cashflows is the result of adjustments made in non-cash items and the changes in operating assets. Thus, the NOCSR of this company under discussion is very high at 7170, as indicated under the maximum value of the ratio. Further, analysis of standard deviation reveals greater variability in profitability, cashflow and non-financial ratios among financially distressed companies relative to the counter group. However, liquidity, leverage and cash flow ratios have relatively greater fluctuations amongst the financially sound companies.

Table 4.6: Random Effects Regression Model Results Summary

				p	95% Confidence Interval	
Variable	β1	β0	β0+β1	value	Upper	Lower
ROA	-14.14182	3.85897	-10.28285	0	1.421408	6.296532
OPR	-8.667558	0.1097698	-8.5577882	0.217	-9.618919	9.838459
CR	-1.11138	1.976117	0.864737	0	1.581854	2.370379
QR	-0.8739867	1.41408	0.5400933	0	1.078574	1.749586
DTAR	0.5890471	0.1430598	0.7321069	0.014	-0.188911	0.4750305
ICR	-40.19116	32.99361	-7.19755	0.068	2.445545	63.54168
TATR	-0.4545233	1.179147	0.7246237	0.002	0.9751751	1.383118
SWCR	-18.78029	21.33416	2.55387	0.041	8.617704	34.05061
NOCSR	26.02957	0.0949487	26.1245187	0.315	-35.83155	36.02144
NOCTAR	-0.0451302	0.0762122	0.031082	0	0.0587694	0.093655
PID	-0.0018238	0.5028178	0.500994	0.914	0.4793678	0.5262678
PPS	-0.0879	0.5842793	0.4963793	0.007	0.5392506	0.6293081

Table 4.6 presents a summary of the dummy variables model developed for each ratio under study. Amongst the ratios considered, eight ratios have emerged to be statistically significant in differentiating a financially distressed company from a financially sound company at 5 percent level of significance. The significant ratios are ROA, CR, QR, DTAR, TATR, SWCR,

NOCTAR and PPS. At 5 percent level of significance, these eight ratios significantly differ between financially distressed and financially sound companies. Therefore, there is enough evidence at 5 percent level of significance to reject H_{01}, H_{03}, H_{04}, H_{05}, H_{07}, H_{08}, H_{10} and H_{12}.

According to the table, the β_1 of DTAR is positive. Positive β_1 for DTAR indicates a direct association of the ratio with financial distress. In other words, greater the ratio higher the probability of financial distress and vice versa. On the other hand, other significant ratios ROA, CR, QR, TATR, SWCR, NOCTAR and PPS have a negative β_1 suggesting an inverse relationship of the ratios with the event of financial distress, i.e., increase in the ratio lowers the probability of experiencing distress and vice versa. As discussed in the research methodology section, the expected value of each ratio for a financially distressed company is the aggregate of β_0 and β_1, and for financially sound company the expected value is is equivalent to β_0. The expected value of each significant measure for the two groups of companies is presented in table 4.6. The table also displays the upper and lower limits of the confidence interval for financially sound companies (β_0) at 95 percent level of confidence. These limits indicate the range within which the ratios of financially sound companies are likely to fall. Thus, the class limits presented in the table can be a good source of direction to the stakeholders in identifying financially sound companies at the time of making investment and lending decisions.

Robustness Check

The robustness of the statistically significant ratios are tested on the training and testing samples. The range within the upper and lower class limits of each ratio for β_0 forms the basis for determining the financial soundness of a company. That is, companies with the value of significant ratios within the class limits are classified as financially sound, and companies with values outside the class limits are classified as financially distressed. The results of the robustness check are presented in table 4.7. The table displays the number of accurate predictions made by each significant ratio and the number of type I and type II error associated with it. Type I error represents the number of financially distressed companies incorrectly predicted as financially sound, and Type II error is the percentage of financially sound companies incorrectly predicted as financially distressed by the primary indicator/ indicators. For the training data, the percentage of prediction accuracy ranges between 76 percent to 56 percent, type I error ranges between 10 percent to nearly 2 percent and type II error ranges between 43 percent to 14 percent. The class limits are considered as the classification criteria

with the aim to minimise the type I error. It is generally agreed upon that the type I errors are more costly than the type II errors when predicting the financial soundness of the business (Gissel, Giacomino, & Akers, 2007). Therefore, the objective is to minimise the type I error and thus, the significant ratio with the consistently minimum type I error is considered as the most efficient ratio and qualifies as the primary indicator of corporate financial distress. According to the results displayed in table 4.7, though, ROA has made the most number of accurate predictions and has the least number of type II errors, CR is more potent in safeguarding the interest of the stakeholders as it has the minimum type I error for training data. Similarly, for the testing sample, ROA has made the maximum number of accurate classifications with the least number of type II error. However, the type I error is least with SWCR followed by CR. The percentage of type I error for CR for both training and testing sample is less than 5 percent thus, making CR the primary indicator of corporate financial distress.

Table 4.7: Results of Robustness Test

Significant Measures	Obs	Accuracy (Nos)	Type I Error (Nos)	Type II Error (Nos)	Obs	Accuracy (Nos)	Type I Error (Nos)	Type II Error (Nos)
ROA	600	453	59	88	220	147	14	59
CR	600	333	9	258	220	121	8	91
QR	600	336	22	242	220	124	10	86
DTAR	600	434	85	81	220	130	35	55
TATR	600	354	32	214	220	121	20	79
SWCR	600	318	36	246	220	115	7	98
NOCTAR	600	330	34	236	220	116	14	90
PPS	600	313	51	236	220	112	29	79

4.3 Objective 3: To investigate the role of non-financial measures in corporate financial distress prediction model.

Two financial distress prediction models are developed Model 1 and Model 2 to test the role of non-financial ratios in corporate financial distress prediction. Model 1 comprises of both financial and non-financial variables as predictors and Model 2 consist of only financial ratios as predictor. Binary logistic Regression analysis is used to formulate the two bankruptcy prediction models.

Before employing logistic regression, the data is checked for the presence of multicollinearity. Multicollinearity causes confusion regarding the relative importance of different independent variables in the model (Wang & Jain, 2003)**.** Correlation analysis is undertaken to detect multicollinearity. Table 4.8 presents the results of the correlation analysis. The table reveals a very high correlation of 0.97 between CR and QR and also a very high correlation of 0.92 between OPR and NOCSR. Thus, QR and NOCSR are eliminated from further process to address the issue of multicollinearity.

Table 4.8 : Correlation Analysis

Variables	ROA	OPR	CR	QR	DTAR	ICR	TATR	SWCR	NOCSR	NOCTAR	PID	PPS
ROA	1.00											
OPR	0.29	1.00										
CR	0.22	0.05	1.00									
QR	0.18	0.04	**0.97**	1.00								
DTAR	-0.07	0.06	0.06	-0.05	1.00							
ICR	0.08	0.01	0.07	0.08	0.01	1.00						
TATR	0.29	0.07	0.07	-0.11	0.04	-0.03	1.00					
SWCR	0.04	0.01	0.04	0.03	0.01	-0.01	0.20	1.00				
NOCSR	-0.19	**0.92**	0.04	-0.03	0.05	0.00	-0.05	-0.01	1.00			
NOCTAR	-0.01	0.33	0.04	-0.05	0.06	0.04	0.08	0.01	0.28	1.00		
PID	0.07	0.07	0.01	-0.02	0.03	-0.06	0.08	0.01	0.06	0.05	1.00	
PPS	0.20	0.02	0.23	0.21	0.04	0.09	0.04	0.05	0.01	0.08	0.04	1.00

The financial distress prediction model is developed based on the random effects approach. The results of logistic regression may be reported as the odds ratio or coefficient. The present study uses the coefficient to understand the type of association between the predictor variable and the probability of financial distress. Table 4.9 presents the logistic regression results of the two models. For Model 1, predictor variables consist of ROA, OPR, CR, DTAR, ICR, TATR, SWCR, NOCTAR, PID, and PPS. The estimated coefficients of ROA, CR, ICR, SWCR, NOCTAR, and PPS are negative, indicating an inverse relationship between the ratios and the probability of distress whereas, OPR, DTAR, TATR, and PID have positive coefficients indicating their direct relationship with the probability of financial distress. However, at a 5 percent level of significance, the association of only three variables, namely ROA, CR and DTAR are statistically significant with the probability of default. The table also reports the Wald chi-square test statistic and the accompanying P-value. The Prob>chi2 is 0.000. As the Prob>chi2 is less than 0.05, the overall model is statistically significant.

Table 4.9: Binary Logistic Regression results

	Model 1		Model 2	
	Coefficient (β)	p-value (sig.)	Coefficient (β)	p-value (sig.)
ROA	-0.5814026	0.002*	-0.1243865	0.357
OPR	0.0161626	0.950	-9.252991	0.205
CR	-7.160657	0.000*	-2.33185	0.001*
DTAR	5.298384	0.014*	2.085215	0.046*
ICR	-0.0257942	0.862	-0.007206	0.858
TATR	0.1875257	0.950	-1.717829	0.114
SWCR	-0.007434	0.582	-0.0048497	0.604
NOCTAR	-23.73184	0.057	-4.71889	0.444
PID	14.41629	0.111		
PPS	-5.327009	0.204		
Constant	-2.820699	0.614	-.1267785	
Wald Chi2		94.24		31.8
Prob > chi		0.00		0.00
Hosmer-Lemeshow Test		0.00		0.00

The predictor variables for Model 2 are ROA, OPR, CR, DTAR, ICR, TATR, SWCR and NOCTAR. Table 4.9 reports the coefficients of ROA, OPR, CR, ICR, TATR, SWCR, and NOCTAR as negative, indicating an inverse relationship with the probability of financial distress. On the other hand, the coefficients of DTAR is positive, demonstrating a direct relationship with the event o fdistress. However, at 5 percent level of significance, the association of only CR and DTAR, are statistically significant with the financial status. The Prob>chi2 is 0.000 for the Wald test indicating statistical significance of the overall model.

Diagnostic Tests

The diagnostic ability of the models are assessed with the aid of ROC, AUC, sensitivity, specificity, type I error, type II error and total annual prediction accuracy The ROC and AUC for the two models are presented in graph 1. The Area Under the Curve (AUC), i.e. area under the Receiver Operating Characteristic (ROC) curve maps the sensitivity against 1-specificity. Sensitivity is the percentage of correctly predicted distressed companies by the model, and

specificity is the percentage of correctly predicted sound companies by the model. The sensitivity and specificity help to estimate the type I and type II error. Type I error is the percentage of distressed companies incorrectly predicted assound, and Type II error is the percentage of sound companies incorrectly predicted as distressed companies. Type I error is computed as (1-sensitivity) and (1-specificity) is the type II error.

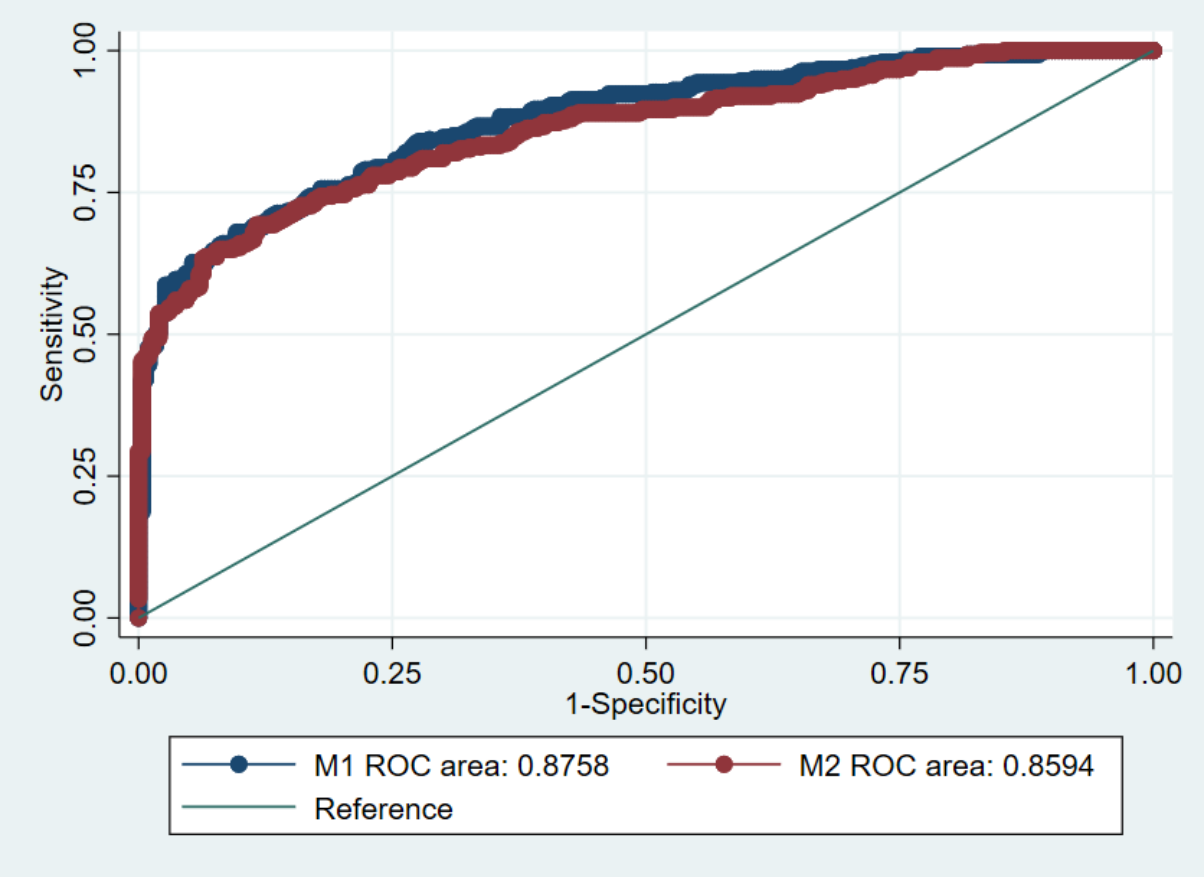

Figure 4.5: Comparative ROC of Model 1 and Model 2

For the formulated models, the ROC and AUC are displayed infigure 4.5. The area under the ROC curve for Model 1 (M1) is 0.8758, whereas Model 2 is 0.8594. AUC indicates the overall classification accuracy of the model. AUC over 80% is very good. Both models indicate a very good ability to predict financial distress. However, M1 with both financial and non-financial measures as predictors have higher AUC, thus, indicating the greater predictive ability of the model.

For a model to classify companies into distressed and sound groups, a cut-off point is required. The z value in the regression equation of each company is compared to the cut-off point to classify the companies into two groups. The present study employs the Liu method to estimate the cut-off point. The Liu method estimates the cut-off point by maximizing the product of

sensitivity and specificity. The estimated cut-off points along with the sensitivity, specificity, and area under the ROC curve at the cut-off point is presented in table 11.

Table 4.10: Empirical cut point estimation

Method:	Liu	Liu
Reference variable:	Status (0=neg, 1=pos)	Status (0=neg, 1=pos)
Classification variable:	M1	M2
Empirical optimal cutpoint:	-4.6314509	-3.7304994
Sensitivity at cutpoint:	0.76	0.69
Specificity at cutpoint:	0.82	0.88
Area under ROC curve at cutpoint:	0.79	0.79

According to the Liu method, as displayed in table 4.10, the optimal cut point for Model 1 is -4.6314509, and Model 2 is-3.7304994. The overall sensitivity at the cut-off point is 0.76, and 0.69 and specificity is 0.82 and 0.88 for Model 1 and Model 2, respectively. The area under the ROC curve at the cut off point for both the models are 0.79 which indicates the total classification accuracy of the two models.

Table 4.11 presents the annual prediction accuracy of the two models at the estimated cut-off points. An overall accuracy of about 79 percent is displayed by both the models. The annual accuracy increases as the year of the bankruptcy filing approach. The overall type I error is approximately 24 percent for Model 1 and 31 percent for Model 2. Type II error is approximately 18 percent and 12 percent, respectively, for Model 1 and Model 2. During the period of five years, accuracy ranges between 90 percent and 67 percent for Model 1, whereas 90 percent and 64 percent for Model 2.

Table 4.11: Annual Classification accuracy of the training sample

		Model 1			Model 2		
Year	Total cases	Total Accuracy	Type I Error	Type II Error	Total Accuracy	Type I Error	Type II Error
1	120	108	4	8	108	6	6
2	120	100	6	14	104	7	9
3	120	98	12	10	98	16	6
4	120	87	23	10	86	27	7

5	120	80	28	12	77	36	7
	600	473	73	54	473	92	35

The total sample is classified as a training and testing sample. For validation, the prediction accuracy of the testing sample is assessed. Table 4.12 presents the annual prediction accuracy of the testing sample. The overall accuracy of Model 1 is greater than Model 2. During the five years, the total accuracy ranges between 80 percent to 60 percent in the case of Model 1 whereas 77 percent to 57 percent in the case of Model 2. The type I error is also lower for Model 1. But, the type II error is lower for Model 2.

Table 4.12: Annual Classification accuracy of testing sample

		Model 1			Model 2		
Year	Total cases	Total Accuracy	Type I Error	Type II Error	Total Accuracy	Type I Error	Type II Error
1	44	34	1	9	33	2	9
2	44	35	1	8	34	3	7
3	44	29	6	9	31	5	8
4	44	26	8	10	26	10	8
5	44	28	8	8	25	12	7
	220	152	24	44	149	32	39

Model 1 Vs Model 2

According to the study results, both the models are statistically significant and are a good fit, as indicated by the Wald Test. Though, the AUC at the estimated cut-off point for both the models is equal at 0.79, Model 1 outperforms Model 2 in three aspects. Firstly, the overall AUC of Model 1 is higher than Model 2 at 0.8758 as against 0.8594. Second, the sensitivity associated with Model 1 is 0.76, resulting in a type I error of 0.24, whereas, the sensitivity for Model 2 is 0.69, and the resulting type I error is 0.31. As discussed, it is generally agreed upon that the type I errors are more costly than the type II errors (Gissel, Giacomino, Akers, 2007). In other words, the amount of loss arising from associating with a company that becomes financially distressed is costlier than the opportunity cost of not associating with a firm that does not get into financial distress contrary to the prediction made by the model. Thus, the model with the smaller type I error and higher sensitivity are ideal. Third, in most of the years

under study, the annual accuracy of Model 1 is either greater or equal to Model 2. Whereas, for testing sample also, the annual accuracy of Model 1 is mostly either higher or equal to Model 2. Also, the Model 1 surpasses Model 2 as the overall accuracy for Model 1 is over 69 percent as against nearly 68 percent for Model 2. Thus, at 5 percent level of accuracy, there is no adequate evidence to reject H_{23} therefore, inclusion of non-financial measures improve the predictive efficacy of the corporate financial distress prediction model. Therefore, Model 1 with both financial and non-financial ratios as predictor variables is recommended for financial distress prediction in the Indian industrial sector. The recommended model forms the supplementary indicator of corporate financial distress in the Indian industrial sector.

4.4 Objective 4: To recommend the indicators of corporate financial distress in the Indian industrial sector.

The indicators of corporate financial distress is presented in the form of a two stage process.

Stage 1: Identify the financially distressed companies using the Primary indicator

The liquidity ratio CR constitutes the primary indicator of corporate financial distress. The liquidity ratios is a crucial measure in determining the ability of a company to pay off its short-term debt obligations. A low current ratio is an indicator of high risk of default. On the other hand, high current ratio though indicates the ability of the company to meet its short-term obligations it is also an indicator of inefficient utilisation of assets. This step is the basic qualifying criteria to be considered before involving in any financial dealing with the company. According to the study results, current ratio ranging between 1.58 to 2.37 is considered to be ideal. Any company with current ratio below 1.58 or above 2.37 is classified as financially distressed.

Stage 2: Verify the financial status of the companies classified as financially sound in stage 1 with the aid of supplementary indicator

The Corporate financial distress prediction model represents the supplementary indicator.

The companies that qualify as financially sound in the first step can be further tested for its soundness using the financial distress prediction model. The financial distress prediction model is as below

z= -2.820699 - 0.5814026 *ROA + 0.0161626 *OPR - 7.160657*CR + 5.298384 *DTAR - 0.0257942 *ICR + 0.1875257 *TATR - 0.007434 *SWCR -23.73184 *NOCTAR + 14.41629

*PID - 5.327009 *PPS

Companies with z value greater than or equal to -4.6314509 is classified as ‘financially distressed’ and z value less than -4.6314509 is continues to have ‘financially sound’ status. After the two stage assessment, companies that emerge as ‘Financially sound’ can be onsidered for lending and investment by the investors and creditors.

The table presents prediction accuracy with which the two stage process successfully indicates financial distress in the Indian Industrial Sector.

Table 4.13: Prediction Accuracy of Indicators of Corporate Financial Distress

Year	Observations	Accuracy (*Absolute*)	Accuracy (*Percentage*)
1	82	82	100
2	82	81	99
3	82	80	98
4	82	75	91
5	82	79	96

Total of 82 companies in the sample were financially distressed and had filed for bankruptcy under IBC. The two stage process successfully identifies all the 82 companies as bankrupt one year prior bankruptcy filing. For two, three, four and five years prior bankruptcy filing 81, 80, 75 and 79 companies were correctly classified as ‘financially distressed’ by the recommended indicators. Thus, according to table 4.13 the recommended Indicators of Corporate financial distress predicts financial distress in the Indian industrial sector at an accuracy ranging between 90 percent to 100 percent during the five years of study.

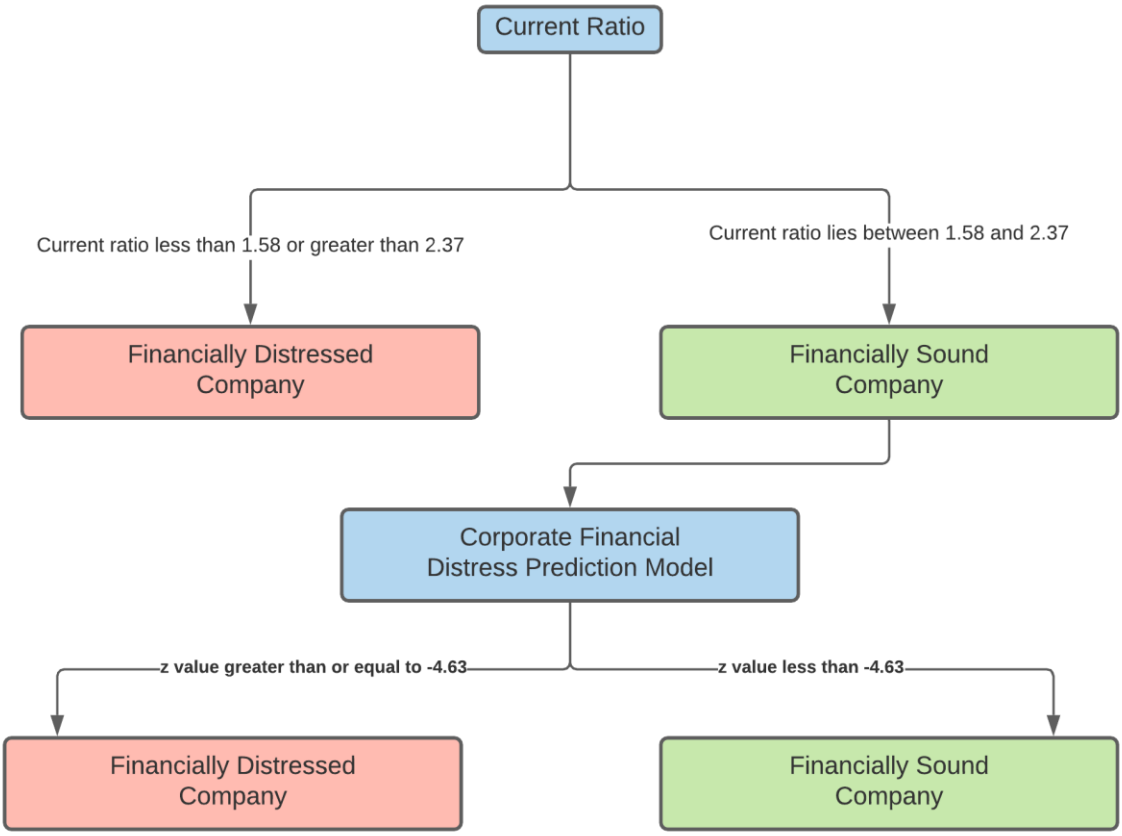
Current Ratio
Current ratio less than 1.58 or greater than 2.37
Current ratio lies between 1.58 and 2.37
Financially Distressed Company
Financially Sound Company
Corporate Financial Distress Prediction Model
z value greater than or equal to -4.63
z value less than -4.63
Financially Distressed Company
Financially Sound Company

Figure 4.6: Indicators of Corporate Financial Distress

5. Findings

The present study begins by assessing the status of bankruptcy filing under IBC and analysing the outcomes of such filings. According to the study results, bankruptcy filing is initiated against 1756 companies. Private sector has witnessed nearly two times the filings of public sector and 5 LLP's have been filed for bankruptcy during the study period. As high as 26 percent of the bankruptcy filings are made in Mumbai bench of NCLT. Mumbai and Delhi benches put together has 49 percent of the total filings. Guwahati bench registers the least number of bankruptcy filings. Amongst the filings made by the three categories of petitioners, financial creditor, operational creditor and corporate debtor, as high as 47 percent of the filings are initiated by operational creditor followed by financial creditors constituting about 43 percent of the filings and lastly about 10 percent of the filings are made by corporate debtors. In the public sector, firms of industrial nature have seen maximum filings. Amongst these filings, manufacturing industry constitutes over 75 percent of the total industrial filings

followed by construction industry and industry dealing with electricity, gas, steam & air conditioning supply.

The outcome of bankruptcy filing is classified into three categories, liquidation, resolution and others. Others include all other cases apart from liquidation and resolution like dismissal, withdrawal and so on. Only 10 percent of the bankruptcy filing cases have seen resolution under IBC whereas, about 40 percent of the defaulting companies have been liquidated. Of the total liquidations made under IBC, maximum number of liquidation decisions are passed by the Mumbai benches followed by Delhi benches and Chennai bench. Trend analysis of outcomes reveals that the overall number of liquidations is increasing year after year while the number of resolutions is declining. In fact, the number of resolutions has halved during the year ended 2019 as compared to 2018. The proportion of liquidation to the total number of filings made by financial creditors is over 40 percent as against about 37 percent by operational creditors. On the other hand, about 12 percent of the filings made by financial creditors have been resolved against over 6 percent resolutions when the petition is made by operational creditors. In all industries, the number of liquidations far exceeded the number of resolutions except the accommodation and food services industry with a total of 11 filings observed two companies being liquidated and two resolved.

The discriminatory power of probability of default models can be examined from the perspective of each factor as well as in terms of the combined performance of all the model factors (Scandizzo, 2016). Ten financial and two non-financial ratios were examined individually for their ability to discriminate between financially distressed and sound companies. Following the analysis, eight ratios, namely ROA, CR, QR, DTAR, TATR, SWCR, NOCTAR and PPS were found to have statistically significant role in determining the financial status of the company. Amongst these eight ratios, liquidity ratio CR has proved to be the consistent and reliable in defining the corporate financial status and thus, emerge as the primary indicator of corporate financial distress in the Indian industraial sector.

A study by Liang, Lu, Tsai & Shih (2016) in Taiwan shows board structure, and ownership structure as most essential non-financial measures along with financial measures in bankruptcy prediction. The present study tests whether these non-financial ratios play a significant role in predicting financial distress in the Indian Industrial sector by considering the Proportion of Independent Directors in the board (PID) and the Proportion of Promoters Share in the capital structure of the company (PPS) along with ten financial ratios. The results of the present study is in agreement with the study conducted by Liang, Lu, Tsai & Shih (2016) in Taiwan, where

the model formulated with non-financial ratios has better predictive efficacy than its counterpart. Therefore, the model recommended for financial distress prediction in the Indian industrial sector comprises of both financial and non-financial measures. The primary indicators along with the financial distress prediction model is presented as a two step process in determining the financial status of a company.

6. Discussion and Implications

6.1 Discussion

The literature points out that an increasing number of companies are filing for bankruptcy under Insolvency and Bankruptcy Code, 2016, and the industrial sector is taking the lead. The present study analyses the bankruptcy filings made under IBC and validates that the number of corporate filings is showing an increasing trend and the industrial sector records the highest number of filings amongst the filings made by the public sector corporations. Further, the analysis of outcomes of bankruptcy filings reveals the number of liquidations is over four times greater than the number of resolutions thus, proving IBC is indeed a creditor-oriented law where liquidation is mostly the outcome of the bankruptcy filing.

Eight of the twelve variables were statistically significant in determining the financial status of the sample companies. They are ROA, CR, QR, DTAR, TATR, SWCR, NOCTAR and PPS. These variables consist of representation from all the six-broad areas of classification of ratios; thus, implying that profitability, liquidity, leverage, efficiency, cashflow and also non-financial measures are all independently powerful in predicting the financial status of a company. According to the present study, profitability ratio ROA has a statistically significant negative association with the event of financial distress, which is in agreement with the study by Singh and Mishra (2016). Similarly, the present study is also in accord with Pervan, Pervan, & Vukoja (2011) and Waqas and Md-Rus (2018) whose research concludes that liquidity ratios CR and QR are negatively associated with the financial status of a company. Likewise, efficiency ratio TATR and cashflow ratio NOCTAR also has an an inverse relationship with the financial status of the company as suggested by Rashid and Abbas (2011) and Waqas and Md-Rus (2018). Further, as suggested by Shetty, Pakkala, & Mallikarjunappa (2012) the present study also confirms a statistically significant positive association of DTAR with the financial status of a company indicating higher the DTAR, greater the probability of experiencing corporate financial distress and vice versa. The results also support the study by Udin, Khan and Javid

(2016), and concludes that insider or promoter ownership have a statistically significant association with the financial status of a company. However, contrary to the findings by Obradovic, Jaksic, Rupic, & Andric (2018) negative association of SWCR with the financial status is observed in the current research. Apart from the contrary result of SWCR, variables like OPR, ICR, NOCSR and PID have indicated a statistically insignificant association with corporate financial distress in the Indian industrial sector. But, of the eight significant ratios, the liquidity ratio CR emerged as the primary indicator of corporate financial distress with the greatest and consistent power to discriminate a financially distressed companies from a financially sound companies.

After comparison of two logistic regression models, M1 and M2, in the recommended model M1, three financial ratios Return on Assets (ROA), Current Ratio (CR), and Debt to Total Assets Ratio (DTAR) have a statistically significant association with the probability of financial distress by the companies. The association of all the statistically significant variables agrees with past studies. That is, ROA and CR are inversely associated with the probability of financial distress, as identified by Singh & Mishra (2016) and Pervan, Pervan, & Vukoja (2011), respectively. As discussed by Shetty, Pakkala, & Mallikarjunappa (2012), DTAR is positively associated with the probability of financial distress. The other financial variables OPR, ICR, TATR, SWCR, NOCSR and NOCTAR's relationship with the probability of financial distress is not statistically significant. Besides, non-financial variables PID and PPS improve the predictive efficacy of the model but does not display a statistically significant association with the probability of corporate financial distress.

6.2 Implications

6.2.1 From the Perspective of Industry Associations

Analysis of the nature and status of the bankruptcy filing, under IBC, indicates an increasing trend in bankruptcy filing over the years in India. The industrial sector, especially the manufacturing, followed by construction, are witnessing major bankruptcy filings. The findings of this study have the potential to provide data that can be utilised by various industry associations like Confederation of Indian Industry (CII), Federation of Indian Chamber of Commerce and Industry (FICCI), the Associated Chambers of Commerce of India (ASSOCHAM) and others to come together and collaborate with the various policymakers from the Ministry of Corporate Affairs (MCA) and Department of Promotion of Industry &

Internal Trade (DIPP) to help create and sustain an environment that is conducive for industrial activities and thus make the industrial sector flourish.

6.2.2 From the perspective of Government of India

The result from the analysis of benchwise bankruptcy filings is of immense use to the Government of India (GOI) while approving additional benches of NCLT. Besides, the analysis of outcomes of bankruptcy filing shows liquidation as mostly the outcome of the insolvency and bankruptcy trial; thus, confirming a creditor-oriented insolvency and bankruptcy law. This can serve as a piece of valuable information encouraging the government to improve the efficiency of the law by striking a balance between debtor and creditor protection. A law that will ensure the continuity of viable firms and liquidation of only unviable firms.

6.2.3 From the perspective of corporate stakeholders

The indicators of of corporate financial distress presented in the form of two step process guide the stakeholders in learning the financial soundness of any company with ease. The primary indicators and the model in the two step process can together serve as a check and recheck mechanism in evaluating the financial status of a company. The recommended indicators can guide the investors in their investment/ divestment decisions and help financial and operational creditors in credit risk analysis. In addition, it can also direct employees in entry and exit decisions, assist the management in strategic planning, and support regulatory bodies in developing an early warning distress mechanism in the Indian industrial sector..

6.3 Limitations

The study has the following limitations

1. In case of bankruptcy filings against any company more than once, only the first filing and the corresponding outcome is analyzed to avoid confusion in choice of financial years preceding the filings.
2. Only, companies with data available for immediately five years preceding the year of bankruptcy filing form the sample for the study. Therefore, the sample size is limited to 82 defaulting and 82 non-defaulting companies.
3. Consolidated financial statements form the basis for data collection. In the absence of consolidated financial statements, the study relies upon standalone financial statements.

4. The study extracts the required financial data from the database Ace Analyzer. The database does not reveal how various items in the financial statements are combined to constitute the financial parameters.
5. The study results may be influenced by extreme values as the study accomodates outlier observations. As these are genuine observations, no effort has been made to treat or alter the extreme values.

6.4 Conclusion & Recommendation for future research

In India, if a business fails, to ensure that the banks and financial institutions, the suppliers, the employees, and all those to whom the business owes money get paid, IBC was formed in 2016. According to IBC, when a business defaults payment, the creditor or the debtor company should file for bankruptcy with the NCLT. A resolution professional is appointed, and the committee of creditors is formed who overtakes the management of the company. Resolution plans are invited. Failure to get a resolution plan will lead to the liquidation of the defaulting company.

The research on IBC filings concludes that an increasing number of companies are filing for bankruptcy, and liquidation is mostly the outcome of bankruptcy filing under IBC proving the law is creditor driven. Further, amongst the three types of petitioners, operational creditors lead in terms of the number of filings made. However, the role of operational creditors is minimal in the insolvency and bankruptcy procedure under IBC as they are excluded from the Committee of Creditors. The explicit exclusion of operational creditors is unique to Indian law. However, recently, the law was amended, stating that the resolution plan shall give priority in payment to the operational creditor over financial creditor.But, the quantum of the amount payable to the operational creditors is subject to the approval by the COC from which the operational creditors are excluded. Thus, the law is not just creditor driven but is biased towards the financial creditors.

The present research identifies and suggests the indicators of Corporate financial distress that can predict corporate financial distress in the Indian industrial sector at an early stage. The indicators comprises of primary indicators and a corporate distress prediction model that has the ability to differentiate financially distressed companies from non-distressed compamies. For any potential stakeholder, planning to invest their time, money, and effort on any company, the recommended indicators are an excellent tool to help predict the probable financial health of the company. Future research can study the role of macroeconomic variables in corporate

financial distress. Further, as the present study only focuses on the Indian industrial sector, researchers can also develop a model exclusive to predict financial distress in the Indian service sector.

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Appendix 1: List of sample companies and their industry affiliation

Defaulting Company	Non-defaulting Company	Industry	Division
Nicco Corporation Ltd	Precision Wires India Ltd	Manufacturing	Electric Equipment
National Steel & Agro Ind Ltd	Jai Corp Ltd	Manufacturing	Basic Metal
Lanco Infratech Ltd	Larsen & Turbo Ltd	Construction	Engineering
Rei Agro Ltd	Hatsun Agro Products Ltd	Manufacturing	Consumer food
Facor Steel Ltd	Prakash Industries Ltd	Manufacturing	Basic Metal
MBL Infrastructure Ltd	Patel Engineering Ltd	Construction	Engineering
Innoventive Industries Ltd	Minda Industries Ltd	Manufacturing	Auto Ancilliary
U B Engineering Ltd	Kabra Extrusiontechnik Ltd	Manufacturing	Machine & Equipments
Era Infra Engineering Ltd	Sadbhav Engineering Ltd	Construction	Engineering
Jyoti Structures Ltd	PTC India Ltd	Manufacturing	Machine & Equipments
INOX Wind Ltd	Gujarat Industries Power Co Ltd	Manufacturing	Machine & Equipments
Meyer Apparel Ltd	Spenta International Ltd	Manufacturing	Textile
Uttam Galva Steel Ltd	Maharashtra Seamless Ltd	Manufacturing	Basic Metal
Hindustan Dorr Oliver Ltd	OM Infraprojects Ltd	Construction	Engineering
Kalyanpur Cements Ltd	Sahyadri Industries Ltd	Construction	Cement & construction Materials
Unity Infra Projects Limited	PNC Infratech Ltd	Construction	Engineering
Ferro Alloys Corporation Ltd	Maithan Alloys Ltd	Manufacturing	Basic Metal
Alok Industries Ltd	Welspun India Ltd	Manufacturing	Textile
Monnet Ispat Energy Ltd	NMDC Ltd	Manufacturing	Basic Metal
Electrosteel Steels Ltd	Jindal Stainless Ltd	Manufacturing	Basic Metal
Amit Spinning Indstries Ltd	Salona Cotspin Ltd	Manufacturing	Textile
Adhunik Metalliks Ltd	KIOCL Ltd	Manufacturing	Basic Metal
Jenson & Nicholsan [India] Ltd	Hardcastle and Waud Manufacturing Company Ltd	Manufacturing	Chemical and chemical products
Jaypee Infratech Ltd	GMR infra Ltd	Construction	Engineering
Shriram EPC	ISGEC Heavy Engineering Ltd	Construction	Engineering
Orchid Pharma Ltd	IPCA Laboratories Ltd	Manufacturing	Pharamceuticals
Ang Industries Ltd	RACL Geartech Ltd	Manufacturing	Auto Ancilliary
SAL Steel Ltd	Kamdhenu Ltd	Manufacturing	Basic Metal
Rainbow Papers Ltd	West coast paper mills ltd	Manufacturing	Paper & paper products
Supreme Tex Mart Ltd	Vishal Fabrics Ltd	Manufacturing	Textile
Gayatri Projects Ltd	Welspun Enterprises Ltd	Manufacturing	Construction
Easun Reyrolle Ltd	Honda Seil Power Products Ltd	Manufacturing	Electric Equipment
Amtek Auto Ltd	Bharat Forge Ltd	Manufacturing	Forgings
Tirupati Inks Ltd	Mysore Petro Chemicals Ltd	Manufacturing	chemical and chemical products
Eastern Gases Ltd	Confidence Petroleum India Ltd	Electricity, gas, steam and air conditioning supply	
Impex Ferro Tec Ltd	20 Microns Ltd	Manufacturing	Basic Metal
Abhishek Corporation Ltd	Amarjothi Spinning Mills Ltd	Manufacturing	Textile
Gujarat Foils Ltd	PG Foils Ltd	Manufacturing	Basic Metal
Metalyst Forgins Ltd	AIA Engineering Ltd	Manufacturing	Forgings

Ruchi Soya Industries Ltd	Gokul Agro Resources Ltd	Manufacturing	Consumer food
Vimal Oils & Foods Ltd	AVT Natural Products Ltd	Manufacturing	Consumer food
Kothari Industrial Corp Ltd	Shiva Global Agro Industries Ltd	Manufacturing	Chemical and chemical products
Rubber Products Ltd	MM Rubber company Ltd	Manufacturing	Rubber
Surana Industries Ltd	Kalyani Steels Ltd	Manufacturing	Basic Metal
Ankit Metal & Power Ltd	Godawari Power & Ispat Ltd	Manufacturing	Basic Metal
Indus Fila Ltd	Lambodhara Textiles Ltd	Manufacturing	Textile
MIC Electronics Ltd	IMP Powers Ltd	Manufacturing	Electric Equipment
Usher Agro Ltd	Heritage foods Ltd	Manufacturing	Consumer food
Diamond Power Infrastructure Ltd	KEI Industries Ltd	Manufacturing	Electric Equipment
Raj Oil Mills Ltd	Kriti Nutrients Ltd	Manufacturing	Consumer food
Ellora Paper Mills Ltd	Ganga Papers India Ltd	Manufacturing	Paper & paper products
Bhushan Steel Ltd	JSW Steel Ltd	Manufacturing	Basic Metal
Mandhana Industries Ltd	Faze Three Ltd	Manufacturing	Textile
Assam Co Ltd	CCL Products Ltd	Manufacturing	Beverages
Castex Technologies Ltd	GNA Axies Ltd	Manufacturing	Forgings
SEL Manufacturing Co ltd	Bombay Rayon Fashion Ltd	Manufacturing	Textile
Shri Lakshmi Cotsyn Ltd	Bombay Dyeing & Manufacturing company Ltd	Manufacturing	Textile
Sterling Biotech Ltd	Torrent Pharmaceuticals Ltd	Manufacturing	Pharamceuticals
Mount Shivalik Industries Ltd	Winsome Breweries Ltd	Manufacturing	Beverage
Camson Bio Technologies Ltd	Super crop safe Ltd	Manufacturing	Chemical and chemical products
Ess Dee Aluminium Ltd	A M D Industries LTD	Manufacturing	Basic Metals
Marsons Ltd	Veto Switchgears & Cables Ltd	Manufacturing	Electric Equipment
Bafna Pharmaceuticals Ltd	Hester Biosciences Ltd	Manufacturing	Pharamceuticals
Parabolic Drugs Ltd	Caplin Point Laboratories Ltd	Manufacturing	Pharamceuticals
Value Industries Ltd	Whirlpool of India Ltd	Manufacturing	Electric Equipment
Rajvir Industries Ltd	Deepak Spinners	Manufacturing	Textile
Sunil Hitech Engineers Ltd	Kalpataru Power Ltd	Manufacturing	Machine & Equipments
Madras Fertilizers Ltd	Deepak Fertilizers & Petrochemicals Corporation Ltd	Manufacturing	chemical and chemical products
Madhucon Projects Ltd	Man Infra Costructions Ltd	Construction	Engineering
Empee Distilleries Ltd	Globus Spirits Ltd	Manufacturing	Beverage
Tara Jewells Ltd	TribhovandasBhimji Zaveri Ltd	Manufacturing	Other manufacturing (jewellery)
B S Ltd	Voltamp Transformers Ltd	Manufacturing	Machine & Equipments
Punj Lloyd Ltd	GVK Power & Infrastructure Ltd	Construction	Engineering
Jaihind Projects Ltd	BL Kashyap & Sons Ltd	Construction	Engineering
Birla Cotsyn [India] Ltd	Winsome Textiles Ltd	Manufacturing	Textile
Khaitan Electricals Ltd	Hawkins Cooker Ltd	Manufacturing	Electric Equipment
Metkore Alloys & Industries Ltd	Adhunik Industries Ltd	Manufacturing	Basic Metal
Govind Rubber Ltd	PTL enterprises Ltd	Manufacturing	Rubber
Pratibha Industries Ltd	IRB Infrastructure Developers Ltd	Construction	Engineering

Sezal Glass Ltd	Saint-Gobain Sekurit India Ltd	Manufacturing	Other non-metallic mineral products (Glass)
Euro Ceramics Ltd	Orient Bell Ltd	Manufacturing	Other non-metallic mineral products (Glass)
The Jeypore Sugar Co Ltd	DCM Shriram Industries Ltd	Manufacturing	Food Products

Appendix 2: Copyright, Publication, Presentation & Best Paper award

Copyright approved

- Received copyright approval from the copyright office, Govt of India for the "Corporate Distress Prediction (CDP) scorecard" in January 2021.

Paper publication status

- Manuscript titled **"**Corporate Default Prediction Model: Evidence from the Indian Industrial Sector" is under review with the journal "Vision: The Journal of Business Perspective" (Sage Publication). The 3nd round of revision in accordance with the recommendations of the reviewer was recently submitted. *(Scopus Journal)*
- Manuscript titled " Key Indicators of Corporate Financial Status: Empirical Evidence from Indian Industrial Sector" is under review at the SCMS Journal of Indian Management. It has currently completed the first level of peer review and the decision is to 'accept with revision'. *(Scopus Journal)*
- Manuscript titled "Corporate Credit Default Prediction Models- A Systematic Review of Research Methodology" is selected for publication in Anvesak (UGC CARE- Group I journal). Publication due by 20th May, 2021.
- Manuscript titled "The role of Board Independence and Ownership Structure in improving the efficacy of Corporate Financial Distress Prediction Model: Evidence from India" presented at the International E-Conference on Advances in Business and Management organised by Shaheed Bhagat Singh College, University of Delhi in collaboration with Tehran University, Iran , Sabaragamuwa University of Sri Lanka is recommended for publication in the Journal of Risk and Financial Management (WOS & ABDC- Ranking)

Paper presentation in conferences

- Presented paper title "Exploring the lead indicators of Corporate Financial Distress- Evidence from India" at the International conference on changing business landscape conducted on 6 and 7 February 2019 at Christ (Deemed to be University), Bangalore.
- Presented paper titled "Predicting Corporate Financial Distress: Evidence from Indian Industrial Sector" at the International conference on Economics and Finance-II

organized on 13 and 14 December 2019 by Narsee Monjee Institute of Management Studies, Bangalore.

- Presented paper titled “The Role of Board Independence and Ownership Structure in improving the efficacy of Corporate Financial Distress Prediction Model: Evidence from India” at the International E-Conference on Advances in Business and Management held during 4 March to 6 March by Department of Commerce, Shaheed Bhagat Singh College, University of Delhi.

- Presented paper titled "Corporate Credit Default Prediction Models- A Systematic Review of Research Methodology" at the International conference on “Future of Business, Management and Economics” on 8th April 2021 organised by G H Raisoni Institute of Business Management in collaboration with Maharashtra Chamber of Commerce, Industry and Agriculture and INSIPRA Research Association.

- Presented paper titled “Key Indicator of Financial Status: Evidence from India” at the International Conference on “Changing Global Economic Landscape: Challenges, Strategies and Business Resilience” during 12-13 April 2021 organised by the Department of Commerce, CHRIST (Deemed to be University)

Best Research Paper Award

- Won the best research paper award for the paper titled “The Role of Board Independence and Ownership Structure in improving the efficacy of Corporate Financial Distress Prediction Model: Evidence from India” at the International E-Conference on Advances in Business and Management organised by Shaheed Bhagat Singh College, University of Delhi in collaboration with Tehran University, Iran , Sabaragamuwa University of Sri Lanka and Emerald Publishing

- Won the best research paper award for the paper titled “Key Indicator of Financial Status: Evidence from India” at the International Conference on “Changing Global Economic Landscape: Challenges, Strategies and Business Resilience” during 12-13 April 2021 organised by the Department of Commerce, CHRIST (Deemed to be University)

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Submission of manuscript

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To: SHILPA SHETTY H 1710072 <shilpa.shetty@res.christuniversity.in>

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I am pleased to inform you that your manuscript completed the first level of peer review at the *SCMS Journal of Indian Management*. The decision was to "**Accept with Major Revisions**." The suggestions after peer review are attached herewith.

Please do send in the revised manuscript by **March 24, 2021** and specify how you have responded to reviewer comments and suggestions in a separate Word document accompanying the revised manuscript.

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Review Comments.docx
19K

Keywords: May include Financial Status, Financial Distress. Ratios should be replaced by Financial Ratios

Literature Review: Research gap is not defined. Research questions are not framed.

Theoretical framework is clear. Basic model is developed.

Objectives to be defined clearly

This is an empirical study and results may be unpredictable.

Conclusion is stated clearly.

Scope of the future study is not specific. The topic is relevant since it deals with investment decisions and risk assessment.

Not able to check the quality of the table, since the data is not available. Quality of the references are ok.

The financial data has been accessed from Ace Analyser and interpreted. Not checked the accuracy of the analysis. Since the data is available in the public portal, it may be a question.

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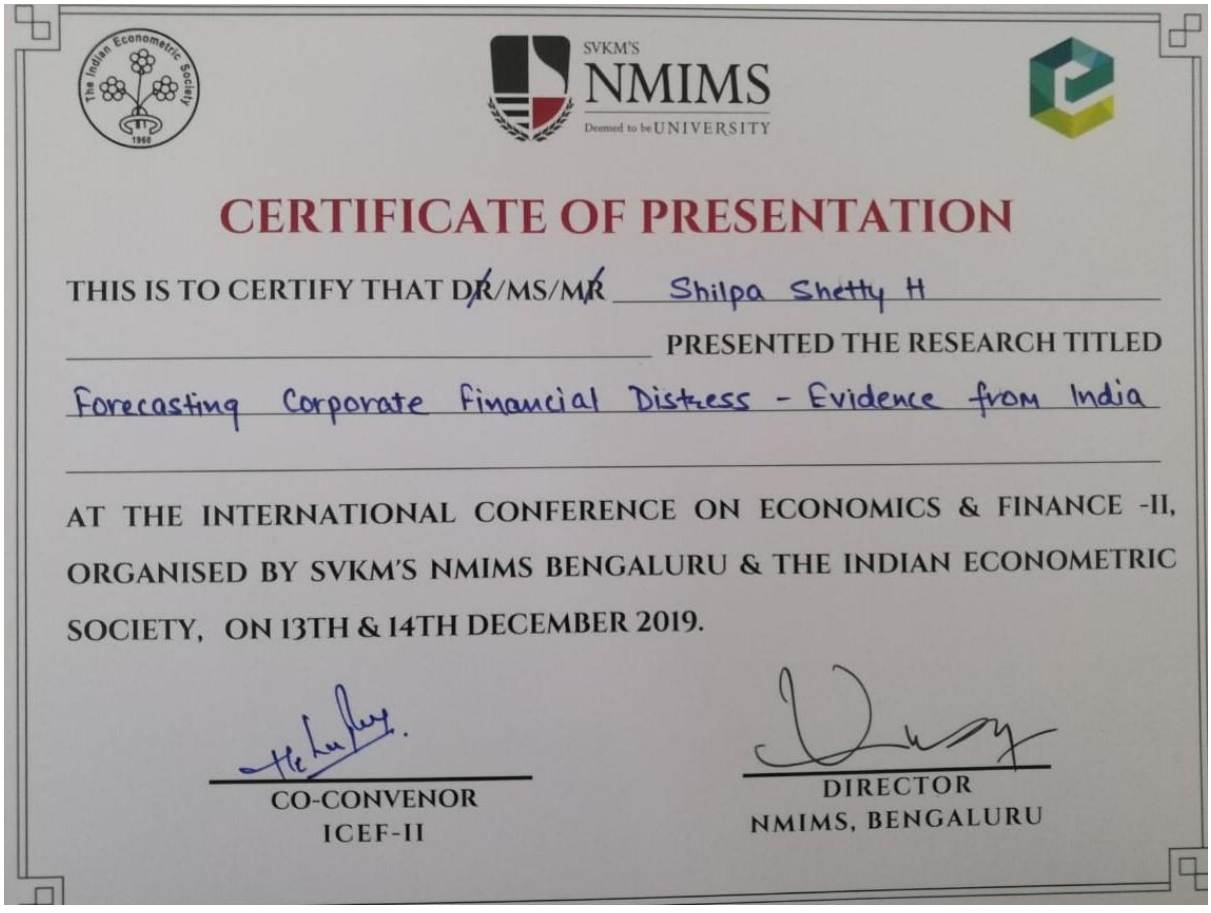

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AT THE INTERNATIONAL CONFERENCE ON ECONOMICS & FINANCE -II, ORGANISED BY SVKM'S NMIMS BENGALURU & THE INDIAN ECONOMETRIC SOCIETY, ON 13TH & 14TH DECEMBER 2019.

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In **FINANCIAL MANAGEMENT** for paper presentation titled

The Role of Board Independence and Ownership Structure in Improving the Efficacy of Corporate Financial Distress Prediction Model - Evidence from India

Presented At

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